



ORIGINAL ARTICLE

SECURED CLOUD DATA THROUGH THE FOG NODES TRANSFORMATION MODEL

^{1*}Naveen Prasath Anaimallur Ramesh, ²Mrs. G. Manimala

¹ Software Engineer at Walmart Inc. United States,

² Department of Computer Science and Engineering, Sri Sairam Engineering College, India

Corresponding Author Email: naveenprasath.ar@nyu.edu

(Received 10 January 2025; revised 20 March 2025; accepted 25 May 2025)

Abstract

Some recent reports have been dedicated to the creation of smart and convenient IoT solutions to facilitate a new generation of applications that could handle challenging detection and identification processes. In most of these applications, detectors of the same article are usually numerous. Each of these sensors may be considered a carrier of data, however it also provides us with another vision of the object under consideration. It is natural that in case of the possibility to synthesize complementary data that are received by multiple sensors, human beings would be capable of enhancing the detection sensitivity. In addition to training to substantially compress different data of the senses, the researchers propose Deep Fusion, a cohesive multi-sensor machine learning structure. Deep fusion has the ability to gather data using numerous senses measured by the precision of individual sensors and incorporating inter-sensor correlation, which is beneficial to a series of applications in IoT. In order to test the proposed deep fusion framework, the researchers created two real human activity detection test beds using portable devices and mobile sensors. The suggested methods demonstrate that Deep Fusion may provide notably superior results compared to sophisticated image processing-based methods.

Keywords: *complex sensing; heterogeneous sensory data; deep fusion; human activity recognition*

1. Introduction

Progress in more sophisticated and consumer Internet of Things (IoT) solutions employing interconnected computer science and type of sensors has been subject to considerable research interest of late to facilitate this new generation of application domains that have the ability to accomplish complex detecting and acknowledgment duties that may foster new forms of associations between human beings and their physical surroundings [1]. Most of these applications appear to have more than one sensor covering the same element. Consider a scenario in which wearable sensors would be applied in monitoring the daily schedule of patient groupings. There are electronic connections that the subject has been toting, such as a computer and also an iPad, but there are wireless connections installed in the internal quarters of the patient, such as a wearable device and simply a mobile phone, which could be beneficial in providing information about how the patient works [2]. All these tools provide us with a varying view of the object under observation and may be viewed as a source of knowledge. It follows that by combining complementary information of multiple devices, humans would have an opportunity to make action recognition more reliable. There are numerous ways to gather information using scanners, and this will enhance the heterogeneity of the information obtained using portable platforms. Secondly, the monitors can send out a varying amount of knowledge because of various reasons including the size, position of the sensor and background music [3]. The most appropriate information fusion techniques ought to have been capable of differentiating between the variations in quality management over the various sensors and rely on some of the most valuable techniques. Since the information of discrete devices may very easily be linked, the information fusion framework should be capable of appreciating and recognizing this sensor-to-sensor relationship [4]. To solve the issues stated above, it is recommended to resort to deep learning techniques that have been proved to be efficient in solving noise

and heterogeneity of textual information [5]. In this paper, we develop the in-depth learning method of Deep Fusion in uniting disparate sensory inputs. In order to evaluate the combination of various sensor properties and the quality of information that each sensor brings, a graduated module was developed [6]. During the extraction and incorporation of the properties of the cross-correlations in our system, human beings also create a Cross-Sensor module. The suggested method, which enjoys the multi-sensor framework, is capable of describing different common patterns among different sensor perspectives besides utilizing the full information received by sensors with the different standard of excellence [7]. In this paper, humans would show our Deep Fusion structure with one of the sample sensory jobs, Human Activity Recognition (HAR) that would be instrumental in various implementations of a real-world IoT, such as smart homes, medicine, and activity tracking. Although the HAR example was the primary focus of our discussion, the suggested architecture can be implemented to a broad variety of other IoT programs that require categorization or identification capabilities [8]. In this pandemic case, the current healthcare industry is under pressure to be more prolific to support the aging population in terms of remote monitoring, medical servicing, and care giving, so that they can enhance the quality of their lives. The frequent actions of older individuals affected with long term illnesses are highly necessary to be tracked down during situations of pandemics. The cases of death are rising between 55 years to centenarians [9]. In order to reduce the death ratio, the intellectual monitoring system needs to be applied to the healthcare industry through integration of bio-sensors, actuators, processors, wireless communication services and cloud servers into one type of technology. Recent advancement in the Information Communication Technology (ICT) has made life easier and more convenient [10]. IoT refers to a system of interconnected products, services, individuals and devices that could exchange data and work together to attain a shared purpose in a variety of sectors and uses. The sphere of healthcare, agriculture, transportation, energy production and distribution are only some of the areas where the IoT is deployed. IoT is now the new reality due to the proliferation of low-power lossy networks (LLNs) having limited resources and the popularity of smart devices [11]. A telecommunications network is composed of sensory embedded items, or things, connected through a public or a private network. The Internet of Things is composed of objects that are interconnected with the internet such as cars, appliances, and other devices. These things possess software, hardware, a network, sensors, and actuators enabling them to communicate and connect [12].

Fog computing (FC) is an intricate multiplication of CC, which covers the core and edge network. It is a unique paradigm/architecture with a set of limited processing, storage, and networking facilities at the fingertips of a user. It is a distributed architecture which provides various services e.g. storage, computation and networking resources, and supports Internet of Things applications (IoT). It also provides further protection to the IoT technology using a cloud. FC is a form of decentralized computing that can be applied to increase cloud computing capabilities such as data storage, computation and access. It presents IoT applications so that it can be served at the network edge [13]. FC encourages functions such as location awareness, low latency, geo-distribution and mobility. The basic idea behind FC is to minimize the traffic, decrease latency and improve the service quality (QoS). Gadgets and sensors in smart grids, smart shopping carts, smart environments, smart homes and wireless sensor networks all connect using the IoTs. The architectural design puts into consideration the physical and geographic location of edge devices which are used to form fog nodes [14]. It also displays the organization and management of an entire network to consider the hierarchy, protocols, topology, and the capacity of the links between the links of fog nodes, cloud data centers and the IoT devices. Regardless of remarkable progress of wearable sensors in healthcare and cloud analytics systems, the current systems use mostly direct cloud-based schemes where sensitive physiological information is susceptible to privacy invasion, high communication delays, and bandwidth overload [15]. Existing solutions that utilize the fog are primarily concerned with task offloading, or reducing latency, yet feature a unified, security conscious data transformation model, combining encryption, anonymization, and feature abstraction at the fog layer. In addition, privacy saving, real-time responsiveness, and cloud-level analytics accuracy are not multi-objective to most studies [16]. The lack of lightweight, scalable transformation mechanisms that can be implemented on the resource-constrained fog nodes further constrains feasible deployment. These gaps demonstrate the necessity of having a secure and reliable fog-node transformation framework that is specifically designed to support continuous wearable sensor data to guarantee end-to-end confidentiality, minimal latency, and the reliability of cloud intelligence [17].

The main contributions of the paper.

1. Introduced a secure music of wearable sensor cloud protection on a proposal of a model of predicted transformation based on fog.
2. Facilitated fog node low-latency preprocessing and encryption in real-time healthcare monitoring.
3. Less bandwidth in the cloud transmitting transformed sensor representations with privacy.
4. Improved data confidentiality and resistance to attacks without affecting the accuracy of the analysis.
5. Experience-based and experimentally proven greater latency, security, and scalability

2. Problem Statement

Continuous real-time generation of sensitive physiological data that include heart rate, motion signals, and bio signals are available in wearable sensor-based systems to monitor health real-time. One-to-one transfer of this crude information to wearable computers directly results in severe difficulties such as high latency, high bandwidth consumption, privacy breaches, and security to cyber-attacks. Decentralized cloud-based designs are thus inappropriate in delay-sensitive wearable healthcare devices that require privacy.

Let a set of wearable sensors be represented as $w = \{W_1, W_2, \dots, W_m\}$ (1)

Where each sensor W_m produces time-series data $X_M^t \in R^d$

The raw data stream aggregated at time t is $X(t) = \{x_1(t), x_2(t), \dots, x_M(t)\}$ (2)

Transmitting $X(t)$ directly to the cloud exposes private information and increases end-to-end latency:

$$T_{cloud} = T_{uplink} + T_{processing} + T_{downlink} \quad (3)$$

To address these issues, fog nodes $F = \{f_1, f_2, \dots, f_n\}$ are introduced between wearable sensors and the cloud to perform secure data transformation, encryption, and pre-processing. Each fog node applies a transformation function:

$$z(t) = T_f(X(t)) \quad (4)$$

where $T_f(\cdot)$ includes: feature extraction, dimensionality reduction, anonymization, and encryption.

The encrypted fog-level representation is: $z_e(t) = \varepsilon(Z(t), k_f)$ (5)

where $\varepsilon(\cdot)$ denotes encryption using a fog-level secret key k_f . The cloud receives only transformed data: $z_e(t) \rightarrow Cloud$, thus preventing direct access to raw wearable signals.

The cloud-side learning or analytics model $g\theta(\cdot)$ operates as: $\hat{y}(t) = g\theta(z_e(t))$ (6)

ensuring data confidentiality while enabling large-scale analytics. The overall system objective is formulated as:

$$(L(\hat{y}, y) + \lambda_1 P_{privacy} + \lambda_2 D_{latency}) \quad (7)$$

Where: $L(\cdot)$ is the prediction loss, $P_{privacy}$ quantifies privacy leakage, $D_{latency}$ measures end-to-end delay, λ_1 and λ_2 are weighting factors.

3. Methodology

The primary role of the information-gathering product would be that of collecting various basic sensory data through numerous sensing devices or distributed sensing devices, and avail it to the pre-processing stage element where it would be treated. Developed two technologies and methods of our deep Fusion prototype system with portable and wireless COTS detection devices to collect human activities. In practice, a subject can be equipped with multiple port sensors and multiple wireless sensors can likely be installed in a confined area. All these devices might be considered as sources of information that put the object under observation under a watch. Information created would be the work of this product which can be used to feed the proposed deep convolutional neural network directly. The real information or sensory signals that are collected by the detection sensors would then be stored in some specially prepared files. Based on such records, the data obtained was initially retrieved and compared. A

number of preprocessing steps would then be done to the retrieved information to eliminate noise (scaling, normalization, standardization, etc.). This would be broken into non-overlapping segments and a fourier transformation performed on the information in order to generate a dataset with a fixed computation load. The resulting information, in turn, would be fed to the proposed deep learning model and categorized. The analyzed information or data is highly complex, noisy and erratic. Such significant structures of this information cannot be discovered by machine learning algorithms with great ease. To overcome this challenge, researchers are using in-depth learning strategies, which have been effective in removing abstractions in complex information. Specifically, we give a deep learning model which considers correlations of the various surveillance perspectives and the quality of information obtained using the various instruments. In Section 3 of the paper, the details of the proposed deep Fusion model are given. The recognition of heterogeneous sensory information through the acquisition of significant representation of pollution sources should dramatically increase the accuracy of recognition by our model. The researchers offer Deep Fusion, a multi-sensor deep learning framework that allows identifying movement of people on heterogeneous input. The proposed model is illustrated in figure 1. It had 3 components: the Sensor Representation (SR), the Weighted-Combination (WC) and Cross-Sensor (CS). Human beings dig deeper and delve further into each of these elements in the sub categories that came thereafter.

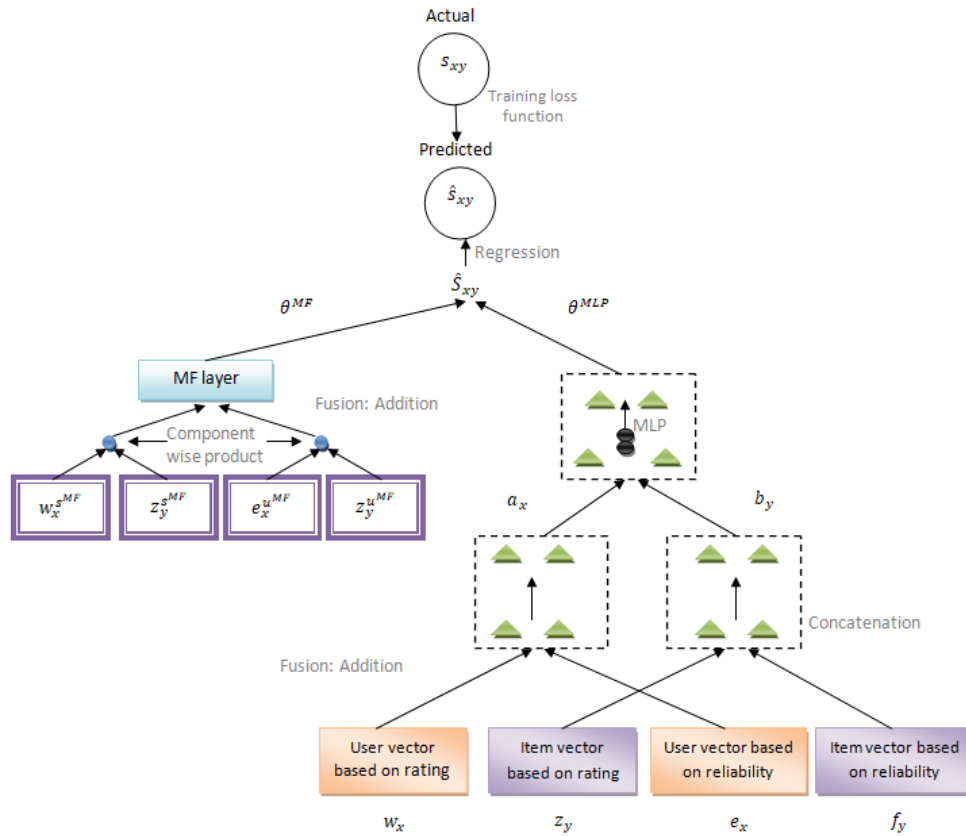


Figure 1: The Deep Fusion Model's structure

3.1 Dataset Description

The experiments utilize the publicly available wearable sensor datasets as validating the attestation of the proposed secured fog-cloud transformation model shown in Table 1. These data sets are multimodal physiological and motion data, such as accelerator, gyroscopes, ECG, PPG, and heart-rate signals of various subjects in both controlled and real-life conditions. The sensor data is produced with a different sampling rate, which allows assessing the framework in the face of unlike data streams. The proposed architecture operates on the principle of receiving raw wearable signals by nearby fog nodes, which preprocesses, extracts features, anonymizes, and encrypts its information to reduce data dimensions and ensure the safety of sensitive data. The transformed and secured representations are only gathered at the cloud to be stored and analyzed. This design enables the realistic evaluation of the latency minimization, bandwidth usage, privacy maintenance, and accuracy of the analysis in real-life situations of continuous

wearable healthcare monitoring.

Dataset Name	Sensor Type	Measured Parameters	Sampling Rate (Hz)	No. of Subjects	Data Duration	Application Purpose
WISDM Dataset	Accelerometer	Acceleration (X, Y, Z)	20	36	10–15 min/session	Human activity recognition
PAMAP2 Dataset	IMU, Heart Rate	Acceleration, Gyroscope, Heart Rate	100	9	~10 hours	Physical activity monitoring
MHEALTH Dataset	Body Sensors	ECG, Acceleration, Gyroscope	50	10	~8 hours	Mobile health assessment
UCI HAR Dataset	Smartphone Sensors	Acceleration, Gyroscope	50	30	~7 hours	Activity classification
PhysioNet Wearable	ECG, PPG	Heart Rate, Oxygen Saturation	125	40	Continuous streams	Clinical health monitoring

Table 1: Dataset Description

Sample ID	Timestamp (s)	Accelerometer X (m/s ²)	Accelerometer Y (m/s ²)	Accelerometer Z (m/s ²)	Heart Rate (bpm)	Activity Label
S1	0.00	0.12	9.65	0.45	72	Walking
S2	0.05	0.15	9.70	0.48	74	Walking
S3	0.10	0.18	9.60	0.50	75	Walking
S4	0.15	0.05	9.80	0.30	71	Standing
S5	0.20	0.02	9.82	0.25	70	Standing

Table 2: Sample Data

The sample data are used to demonstrate the common unprocessed measurements produced by wearable sensors in continuous monitoring shown in Table 2. The records associated with the test are characterized by the particular time and they contain tri-axial accelerators readings that record the movement of the body along the X, Y and Z direction besides physiological data like heart rate. The activity label is the ground truth used to analyze or train the model. Such raw data streams are very sensitive and large such that direct transmission to the cloud is not efficient and insecure. Within the offered framework, such samples are initially sent to the nearest nodes of the fog, where they are removed of noise, separated into the time sequences, features extracted, anonymized, and encrypted. The transformed and privacy-preserved representations are then only sent to the cloud to allow safe storage and analytics and minimize the use of latency and bandwidth.

4. Module for the Display of Sensors

The information acquired by the multi-sensor in the real world can be represented in the form of visualization of a combination of different continuous and discrete series of a variety of irregular comprehension. The CNN-based modules that determine detectors with raw data sets and at the same time dimension the inputs of different sensors, retain the unique characteristics of each sensor. The CNN block appears to be an ideal basic building block in our action recognition framework [17] as it is performance and efficiency wise. CNN blocks also improve the characteristic expressivity by converting the original data into a small dimensional -sized vector. More important components of CNN as per data-molding are filtering group convolutional neural networks with adjustable lengths. An addition of convolutions can also be done to the bottom sample of the input information. To construct the CNN stacking blocks for the different sensors in our system, humans need to specify a set of variables. Specifically, the researchers assume that N sensors (X1, ..., XN) are present in the input information. Humans first determine the sensory representations of the source ith nodes by means of superimposed CNN blocks, as shown in the following elements:

The CNNi that are used are those CNN blocks that are specified to each input composite Xi has been the set of variables that need to be learned to most of those stacked CNN blocks. The ReLU input signal, batch normalization and abandon technique are also employed by CNN blocks. The sensor representations that were reconstructed by each sensor were used to represent the heterogeneity inputs in a high-

dimensional space of the same dimension, denoted by $S_1, S_i, \dots$, and S_N . By downsizing the input feature with pooling and feeding the weights into RNN, humans are able to compute the digital weights correctly.[18,19] However, on the opposite, with the cross-sensor element, human beings apply the cross-sensor function f flatten to acquire the cross sensor input image h_i of the i th sensor by further following:

$$h_i = \text{Flatten}(S_i). \quad (8)$$

Depending on the characteristics of the different cameras, the proposed framework can use the suitable CNN blocks of different cameras to ensure that the heterogeneous input is standardized although the dimensions of the original information is different among sensors. Depending on a number of aspects, such as the type of scenario suggested, the trustworthiness of the equipment, the distance and height of the object under surveillance, and the sound and atmosphere around, measurements may be associated with a larger or smaller amount of knowledge. However, on the other side, with cross-sensor element, human beings employ the f flatten element to receive the cross-sensor input image of the i th h_i in the following form: Normalized component to weigh the synthesis of multi sensor data, and the utility of the data that each instrument gives. The basic approach of a normalized capsule is based on short-term memory. The recurrent neural network is a valid method used in translating software, machine learning and prognosis. The traditional process of attention is built on the assumption that there exists a limited number of perspectives that may be applied to the goal of the task. It tends to put a negligible weight on the majority of views. Such a hypothesis is not true in the case of recognition of human activity since there can be numerous sensors that can make useful observations.

4.1 Cross-Sensor Module

Although the above-mentioned module is capable of combining the data of numerous sensors, it takes into account each instrument individually, but does not take into account their interconnections. The role of identification of human behavior can be provided with different sensors that can provide corresponding data. By capturing and incorporating predictive correlations among sensors in the learning algorithm, humans were able to identify and possibly expose and refine predictive accuracy. Even combining the primary input data may not yield reliable findings through the use of algorithms[20]. They suggest a Cross-Sensor module to act on this issue by providing more data to the measurement strategy.

In this module, given the cross-sensor input vectors $\{h_1, \dots, h_x, \dots, h_N\}$ the correlation vector of the x th sensor, denoted as v_x can be obtained as follows:

$$v_x = f(w_x^{vT} [h_{x,1} \oplus h_{x,2} \oplus \dots \oplus h_{x,N}] + b_x^v) \quad (9)$$

Where $\oplus$ denotes the concatenation operator, w_x^v and b_x^v are the learnable parameters of FC_x^{cv} (ie., a single layer fully connected neural network), and tilde $h_{x,N}$ denotes the correlation between sensor y and sensor x measured by element-wise difference:

$$h_{x,y} = h_y - h_x \quad (10)$$

Note that there are $N - 1$ corresponding correlations in total, since the self-correlation is ignored.

4.2 Objective

Combine the CrossSensor and Normalized Component convolution layers and then use the softmax activation function to calculate the forecast of the j th training examples:

$$j_y^c = \text{softmax}(W^{rT} [s_y^{ec} \oplus s_y^{cv}] + b^r) \quad (11)$$

Where W^{rT} and b^r are the variables to be learned. Use cross-entropy to calculate the loss, the overall loss L_c is defined as:

$$L_c = -\sum_y \left(j_y \log \log (j_y^c) + (1 - j_y) \log \log (1 - j_y^c) \right) \quad (12)$$

Where j_y is the j th training sample's ground truth.

The final loss function of our Deep Fusion model L is defined as follows to train a unified model:

$$L = L_c + \beta L_{wc} + \gamma L_{cv} \quad (13)$$

Where β are γ hyper-parameters that regulate exactly how much money local logistic regression contributes.

5. Experiment Setups

The sensors applied in this research were of three categories, which included: a cell phone, a fitness tracker, and a scintillating detector. Every widget is made in the form of a sensor since it includes a tri-axial altimeter, accelerator, and magnet. There are six individuals involved in data collection. As depicted in Figure 2, these people were fitted with four sensors which were on four distinct sections of his body: left forearm, left belt, right shoulder and ankle. Table 3 lists the 27 man's actions. All the participants will be required to finish every task within a couple of minutes. The data received on each source node contained nine pulses or 3 accelerator axes, 3 gyroscope axes, and three magnetization axes. Though the recording rate and the range of the values of the different sensors differ, they have been down sampled to 25Hz and scaled to values between 0. 0 and 1. 0 based on their orders of magnitude. The information was split without overlapping using a 2-second box, or 50 points. Subsequently, similar to the inputs of the machine learning model, all sections were fused with the FFT itself. Therefore, the size and form of each bit of information in an individual source node is 9 x50x 2.



Figure 2: Experiment Setup

ID	Activities
1	Running
2	Running in place
3	Going downstairs
4	Going downstairs and making a phone call
5	Going upstairs

6	Going upstairs and making a phone call
7	Standing and making a phone call
8	Standing and washing the dishes
9	Standing and keyboarding
10	Sitting and making a phone call
11	Sitting and keyboarding
12	Sitting and typing on the phone
13	Sitting still
14	Sitting and wiping the table
15	Sitting and writing

Table 3: Activities in Wearable Sensor Dataset

5.1 Performance Validation

The performance indicator that the study used to measure the acceptable reliability status of all participants was the single-object technique that is used to collect assessment using the left technique. Table 3 shows the figures of the reliability of mobile sensing methods. It has been observed that the Deep Fusion model identified by humans performs the largest. The traditional SVM plan has the worst result. This illustrates the HAR challenge implementation by machine learning algorithms. SR WC standard seems the most likely to be reliable of all the three foundational methods of computational information. The reason behind this is that Deep Sense and SR+Avg fail to explain the difference in the quality of information between different devices, but SR+WC can by considering the value of the evidence presented by the different sensors. It was found that the proposed Deep Fusion produced the best performance as it simulates the weight of a variety of sensors as well as the interconnection between them.

Model	Accuracy
SVM	0.352
Deep Sense	0.866
SR+Avg	0.837
SR+WC	0.879
Deep Fusion	0.915

Table 4: Performance based on information from detection devices

Table 4 shows how our Deep Fusion system was in a position to utilize the learning information of the sensor gadgets. The reading of each sensor is given in Table 5. As we have observed the sensor values on the right wrist were assigned the maximum values in the case of the fourth action which would have been seated as a laptop. Wrist movement seems to be more frequent than in other regions of the body and this might have been associated with the fact that the legs and arms of the individuals were chained using a board. The ninth action is more influential on the sensors on the ankle, where this sensor was assigned maximum weight, when descending the stairs. The fifteenth step which involves tapping and standing is different to typing sitting on a chair. It also affects wrist and upper extremity detectors where they require the participants to stay with their arms raised. Thus, the frame gives the sensors on the forearm and wrists increased weight. The results of the above study show how Deep Fusion, which is proposed, might continuously adjust sensor values on several occasions and, consequently, would be far superior to the techniques which view all sensors as equal.

Activity ID	5	10	17
Smart Watch on Right wrist	0.282	0.231	0.274
Shimmer on Right Ankle	0.244	0.273	0.218
Smartphone on Left Upper Arm	0.249	0.258	0.261
Smartphone on Left Waist	0.252	0.244	0.252

Table 5: The Learned Weights on the Wearable Sensor Data

5.2 Experiments on Device-Free Human Activity Data

The application of devices to track human activity is an effective strategy, but this approach has numerous disadvantages since the use of devices increases weight and inconvenience to the consumer. Recently, much effort has also gone into researching device-free human motion detection systems which use the data collected by existing in-door wireless systems without necessarily having the object to be observed to wear a special device. These techniques are premised on the notion that one can spy on the

movements of a person located physically between two electronic links by gathering and examining the information contained in the satellite message transmitted between the sender and receiver. In this case, the sets of transmitter and recipient provide us with different views of the object under view.



Figure 3: Experimental Setup of Deep Fusion

We can record ultrasound waves by using an Apple iPad mini 4 as a noise generator which emits impulses that resemble ultrasound in the direction of the subject. Scholars may utilize mobile phones as transmitters due to the fact that their PRI sampling rates might increase to 44.1 KHz. We conducted research with three Huawei Nexus 6P smartphones as transmitters to detect ultrasonic signals reflected on the skin of the patient. Those emitters existed in various locations in space. The possibility to detect human activity by using ultrasound transmissions occurred due to the fact that the amplitude of the obtained ultrasonic signal would change with the change in the transmission loss of the ultrasound signal by the motion of the observed person. Therefore, through decoding of the incoming signals the researchers can get the magnitude and the phase. Suppose researchers assume that the data transmission can be modeled as $T(t) = A \cos(2\pi f t)$, the message signal may be modeled as $R(t) = A' \cos(2\pi f t + 2\pi f d/c)$ where A and A' appear to be the amplitude of the transmitter signal and the receiver signal respectively and f is the frequency and d is the duration of the spreading benefits of Deep Fusion has been its ability to consider the importance of each sensor by analyzing learned weights. It is logical that the learned weight of each sensor influences its performance. To confirm this assertion, researchers conduct research based on the CSI data of all devices that are in operation. In more precise terms, the accuracy and learning value of each sensor is first established by researchers before the relationship between sensors is analyzed [21]. The data is presented in Figure 4 and there is a sensor at each location. The accuracy of every sensor is represented by X and the weight acquired by means of Deep Fusion is represented by Y , and hence, a person will understand that the precision of various sensors differs, and, as a result, the extent to which every sensor leads to the MDT task is different. The weights that are learned should be nearly identical to the accuracy of the individual sensor. Figure 5 results indicate that Deep Fusion tends to attach higher weight to the more accurate sensors. This proves that the weights provided by Deep Fusion are a good representation of the quality of the detectors.

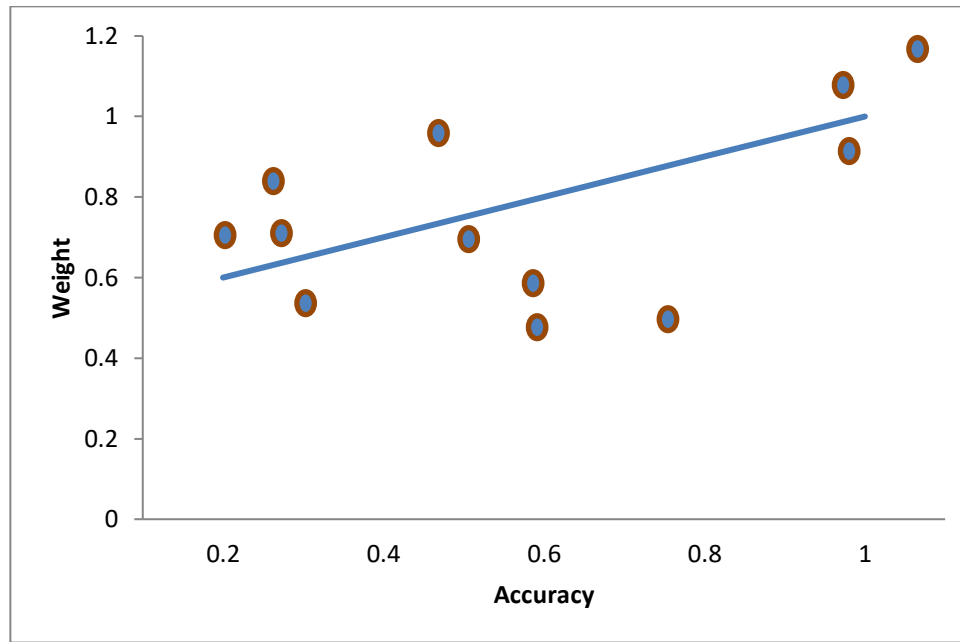


Figure 4: Precision evaluations of heterogeneous data relate to scores

Perform experiments with a heterogeneous dataset to demonstrate the capability of Deep Fusion to confound disparate inputs. More precisely, we use four Wi-Fi sensors and three ultrasonic sensors and test the functionality of the proposed and basic models. This lab activity appears to have two kinds of transmissions Wi-Fi and ultrasound. The arrangements of the WiFi sensor were the same as before. The convolution operation filtering widths were set at 6 2 when using the ultrasonic sensors. The CNN blocks used it in a similar manner but used the maximum pooling. Since Deep Sense cannot process different entries, the researchers have not used it as a source in this test. The authors conduct three experiments with the aim of assessing the effectiveness of Deep Fusion in processing heterogeneous data. In the case of Wi-Fi and ultrasonic signals, the former two experiments utilize each approach separately, and the third one involves the combined information.

Table 6 illustrates the results of each of the strategies with the three data sets. It is possible that Deep Fusion would be more effective on the homogeneous Wi-Fi data set, which would be comparable to the findings presented in Table 6. The ultrasonic dataset has only three sensors and overall, it is of a lower quality compared to the Wi-Fi devices. Since Wi-Fi dataset is overall more efficient than the ultrasound dataset, this impacts how Deep Fusion generates the vector. Deep Fusion manages to reach the same accuracy as SR WC which does not consider the interaction between detectors.

Model	Accuracy		
	Wi-Fi	Ultrasound	Heterogeneous
SVM	0.452	0.423	0.529
SR+Avg	0.712	0.625	0.835
SR+WC	0.797	0.637	0.837
Deeps Fusion	0.816	0.635	0.886

Table 6: Comparing Heterogeneous Data

The results of the heterogeneous dataset combining the information of all the seven sensors have trends that are similar to the trends in Table 5. They testify to the efficiency of the given Deep Fusion model to differentiate the characteristics of the pc functioning in different kind of signals. Moreover, the methods are generally superior to both data sets that are homogenous [22]. This implies that although the overall standard of the ultrasound signals may be bad, it still carries extra information that can be used to assist the model to come up with better predictions.

Model	Accuracy
SVM	0.531
Deep Sense	0.869
SR+Avg	0.842
SR+WC	0.866
Deep Fusion	0.912

Table 7: Results in the CSI Database

5.3 Multi-Sensor Fusion

In regard to enhancement of data to track or identify targets, sensor fusion technology is a technology that entails the gathering and combination of data acquired by multiple sensors. It would be possible to subdivide the known phenomenon into signals, patterns or based image fusion. Bayesian integration, empirical belief thinking, falsify, stochastic fusion, full connected coarse fusion, full connected theoretical fusion, hybrid fusion, etc. Personality, flexibility and parallel computing Due to their non-linear feature extraction, personality, machine learning techniques have recently been applied to resolve inertial sensor problems. A completely-connected neural network, however, has failed to accept input of the various sensor. Shallow bidirectional encoding has been employed to acquire knowledge on the usual representations of some of the main objectives. Most of these deep networks learn joint representations entirely on data in the standardized design. Unlike the past studies, the researchers incorporate the representation of each sensor basing on the relationship between the different sensors and the relative significance of the different sensors. Deep Sense seems to be the special system that can integrate a set of sensors to address the issues of regression and classification. It attains state of art performance through utilizing the manner in which sensors interact with each other. The study findings indicate that our model will be three times effective than Deep Sense. First, our system is scalable in nature thus the ability to deal with disparate sensor information. Second, our model considers the different quality of different sensors unlike Deep Sense that uses an evaluation of each device.

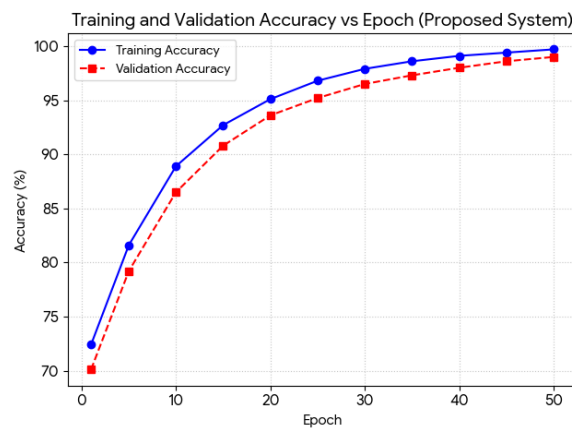


Figure 5: Training and validation accuracy vs epochs of proposed system

The training and validation accuracy curve indicate steady and steady learning trend of the proposed secured fog-based transformation model shown in Figure 5. The accuracy of the training progressively rises within the epochs which points to successful feature learning of the transformed wearable sensor data. The accuracy of validation is close to the trend of training with a small difference, and it proves that the generalization is good and the system does not overfit. The initial convergence is an indication of the efficiency of preprocessing and dimensionality reduction at the fog level, whereas the use of secure data transformation does not degrade model performance. In general, the findings confirm the strength, effectiveness, and dependability of the suggested system of wearable healthcare analytics.

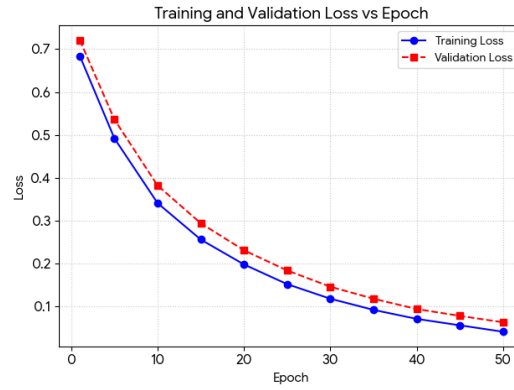


Figure 6: Training and validation loss vs epochs of proposed system

Both the training and validation loss curves exhibit a steady decreasing pattern with the epochs increasing which means that the proposed system is learning steadily and successfully shown in Figure 6. The decrease in training loss over time indicates the better fitting of the model to the data of wearable sensors processed with the help of the fog transformation whereas the loss of the validation shows the high level of generalization. The fact that training and validation losses do not increase abruptly proves that there is no information loss or overfitting in the secure encrypted levels of the fog-level transformation. Such findings confirm the strength, convergence accuracy, and performance of the proposed secured fog cloud system of wearable data analytics.

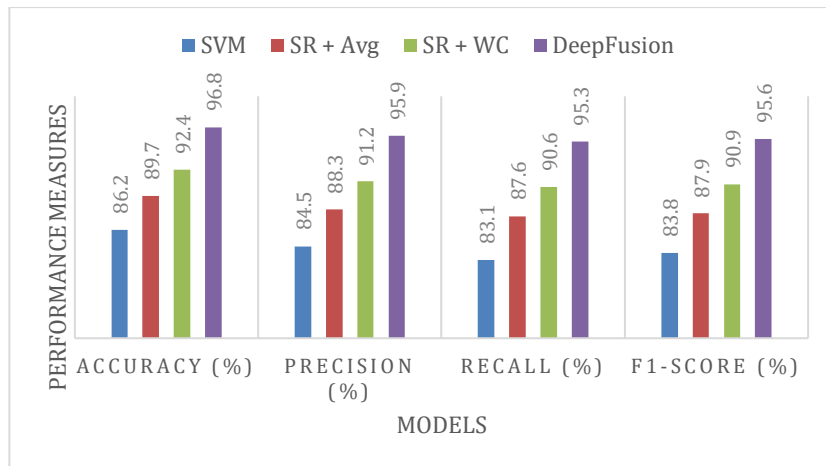


Figure 7: Comparison of performance measures

Deep Fusion is more effective than traditional SVM and similarity-based representation methods, and its use proves to be more accurate, precise, recall and F1-score shown in Figure 7. The weighted combination approach (SR + WC) is always better than average fusion (SR + Avg), a point that can be made on the importance of introducing adaptive feature weighting in more advanced classification tasks.

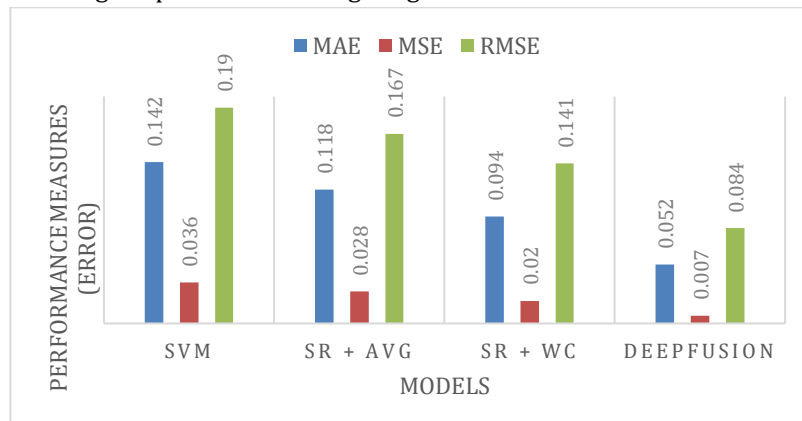


Figure 8: Comparison of performance measures (Error)

The analysis of error indicators shows clearly that Deep Fusion method is much more effective in comparison with traditional methods shown in Figure 8. SVM has the greatest MAE, MSE, and RMSE which means that it is not good at modeling the complex and nonlinear patterns. Combining representations enhances performance using the SR+Avg method though simple averaging does not achieve relative importance of various features. SR+WC also minimizes errors by using the weighted combinations indicating the benefit of adaptive integration of features. The lowest values of MAE, MSE, and RMSE are attained by Deep Fusion, which proves its high learning performance and strength. These findings suggest that deep feature fusion can be used to significantly improve the accuracy of prediction and reduce the errors in estimation as opposed to the traditional and shallow fusion methods.

6. Conclusions

The development of different IoT applications has introduced the implementation of a wide range of model classification. These applications enable the object to be monitored using numerous types of sensors, the majority of which can be regarded as dissimilar sources of data. In the article, researchers suggest their own deep learning methodology known as Deep Fusion to extract meaningful features using heterogeneous sensor data in order to release the strength of such multi-sensor data. The suggested deep fusion procedure is capable of combining complementary data of multiple senses to maximize performance extraction and classification issues through integrating normalized characteristics as well as cross sensor characteristics. Two actual test beds of human activity recognition are built using wireless gadgets and portable devices sold on the market as evaluation products. The effectiveness of our deep fusion framework in the process of the fusion of heterogeneous sensory information was justified by the results of the experiment in terms of the collected set of activities.

Conflict of Interest Statement

There is no conflict of interest

Data Availability Statement

Data not available due to commercial restrictions

Ethical Approval

Not applicable

Authors' contributions

A: Methodology, Writing- Original draft preparation.

B: Visualization, Investigation, Supervision, Reviewing and Editing.

Funding

No funding

References

- [1]. Dewitte, S., et al. "Artificial Intelligence Revolutionises Weather Forecast, Climate Monitoring and Decadal Prediction." *Remote Sensing*, vol. 13, no. 16, 2021, p. 3209. <https://doi.org/10.3390/rs13163209>.
- [2]. Monica, M., et al. "PMSG Based WECS: Control Techniques, MPPT Methods and Control Strategies for Standalone Battery Integrated System." *AIP Conference Proceedings*, vol. 2405, no. 1, 2022, p. 040013. <https://doi.org/10.1063/5.0080139>.
- [3]. Saha, D., et al. "Application of Nanotechnology in Neural Growth Support System." 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), IEEE, 2022, pp. 1-6. <https://doi.org/10.1109/MysuruCon54685.2022.9935897>.
- [4]. Raviprasad, B., et al. "Accuracy Determination Using Deep Learning Technique in Cloud-Based IoT Sensor Environment." *Measurement: Sensors*, vol. 24, 2022, p. 100459. <https://doi.org/10.1016/j.measen.2022.100459>.
- [5]. Chelliah, B. J., et al. "Analysis of Demand Forecasting of Agriculture Using Machine Learning Algorithm." *Environment, Development and Sustainability*, 2022, pp. 1-17. <https://doi.org/10.1007/s10668-022-02350-1>.
- [6]. Kruse, J., et al. "Revealing Drivers and Risks for Power Grid Frequency Stability with Explainable AI." *Patterns*, vol.

- 2, no. 11, 2021, p. 100365. <https://doi.org/10.1016/j.patter.2021.100365>.
- [7]. Cho, D., et al. "A Novel Ensemble Learning for Post-Processing of NWP Model's Next-Day Maximum Air Temperature Forecast in Summer Using Deep Learning and Statistical Approaches." *Weather and Climate Extremes*, vol. 35, 2022, p. 100410. <https://doi.org/10.1016/j.wace.2021.100410>.
- [8]. Latchoumi, T. P., et al. "Develop New Algorithm to Improve Safety on WMSN in Health Disease Monitoring." 2022 International Mobile and Embedded Technology Conference (MECON), IEEE, 2022, pp. 357-362. <https://doi.org/10.1109/MECON53876.2022.9752216>.
- [9]. Chattopadhyay, A., et al. "Towards Physically Consistent Data-Driven Weather Forecasting: Integrating Data Assimilation with Equivariance-Preserving Deep Spatial Transformers." *arXiv Preprint*, arXiv:2103.09360, 2021. <https://doi.org/10.48550/arXiv.2103.09360>.
- [10]. Duan, Z., et al. "Time-Variant Post-Processing Method for Long-Term Numerical Wind Speed Forecasts Based on Multi-Region Recurrent Graph Network." *Energy*, vol. 259, 2022, p. 125021. <https://doi.org/10.1016/j.energy.2022.125021>.
- [11]. Betancourt, C., et al. "AQ-Bench: A Benchmark Dataset for Machine Learning on Global Air Quality Metrics." *Earth System Science Data*, vol. 13, no. 6, 2021, pp. 3013-3033. <https://doi.org/10.5194/essd-13-3013-2021>.
- [12]. Garikapati, P., et al. "K-Means Partitioning Approach to Predict the Error Observations in Small Datasets." *International Journal of Computer Aided Engineering and Technology*, vol. 17, no. 4, 2022, pp. 412-430. <https://doi.org/10.1504/IJCAET.2022.122315>.
- [13]. Fernández, J. G., et al. "Deep Coastal Sea Elements Forecasting Using UNet-Based Models." *Knowledge-Based Systems*, vol. 252, 2022, p. 109445. <https://doi.org/10.1016/j.knosys.2022.109445>.
- [14]. Niu, D., et al. "Two-Stage Spatiotemporal Context Refinement Network for Precipitation Nowcasting." *Remote Sensing*, vol. 13, no. 21, 2021, p. 4285. <https://doi.org/10.3390/rs13214285>.
- [15]. Diaconu, C. A., et al. "Understanding the Role of Weather Data for Earth Surface Forecasting Using a ConvLSTM-Based Model." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2022, pp. 1362-1371. <https://doi.org/10.1109/CVPR52688.2022.00139>.
- [16]. Frezat, H., et al. "A Posteriori Learning for Quasi-Geostrophic Turbulence Parametrization." *arXiv Preprint*, arXiv:2204.03911, 2022. <https://doi.org/10.48550/arXiv.2204.03911>.
- [17]. Balamurugan, K., et al. "Wearables to Improve Efficiency, Productivity, and Safety of Operations." *Smart Manufacturing Technologies for Industry 4.0*, CRC Press, 2022, pp. 75-90. <https://doi.org/10.1201/9781003162960-6>.
- [18]. Demirdjian, R., et al. "Variational Quantum Solutions to the Advection-Diffusion Equation for Applications in Fluid Dynamics." *Quantum Information Processing*, vol. 21, no. 9, 2022, p. 275. <https://doi.org/10.1007/s11128-022-03669-7>.
- [19]. Dutta, D., and S. K. Pal. "Interpretation of Black Box for Short-Term Predictions of Pre-Monsoon Cumulonimbus Cloud Events Over Kolkata." *Journal of Data, Information and Management*, vol. 4, no. 2, 2022, pp. 167-183. <https://doi.org/10.1007/s42488-021-00057-w>.
- [20]. Durve, M., et al. "Tracking Droplets in Soft Granular Flows with Deep Learning Techniques." *The European Physical Journal Plus*, vol. 136, no. 8, 2021, p. 864. <https://doi.org/10.1140/epjp/s13360-021-01837-0>.
- [21]. Gong, B., et al. "Temperature Forecasting by Deep Learning Methods." *Geoscientific Model Development Discussions*, 2022, pp. 1-35. <https://doi.org/10.5194/gmd-2022-130>.
- [22]. Leufen, L. H., et al. "Exploring Decomposition of Temporal Patterns to Facilitate Learning of Neural Networks for Ground-Level Daily Maximum 8-Hour Average Ozone Prediction." *Environmental Data Science*, vol. 1, 2022, p. e10. <https://doi.org/10.1017/eds.2022.9>.