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Smart-Monitor: Patient Monitoring System for IoT-Based Healthcare System Using Deep Learning

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ABSTRACT
Automated physiological signal monitoring to elderly sick patient is not only for fast access of data but also to get reliable service by accurate prediction by healthcare service provider. To address this challenge, this research focuses on novel Internet of Things (IoT) application-based physiological signal monitoring system to advance e-healthcare system. For the realization of the proposed system, Deep Neural Network-based accurate Signal Prediction and estimation algorithm was employed. The proposed system is prototyped as an advanced electronics component by using an intelligent sensor for signal measurement, National Instrument myRIO for smart data acquisition. Smart-Monitor is designed with intelligent sensor as the consumer product. To validate the proposed Smart-Monitor system, four physiological signal prediction accuracies for two users were computed. In prototype experimental set-up, an average accuracy of 97.2% was obtained. This shows that the proposed automated system is reliable and accurate monitoring is possible. From the experimental result, we validate the proposed system can provide reliable assist and accurate signal prediction.

KEYWORDS
Internet of Things; Deep learning algorithm; Elderly care; Smart healthcare; Patient monitoring

1. INTRODUCTION

Reliable physiological signal monitoring is a conventional problem in healthcare system. Body Sensor Network (BSN)-based monitoring system is designed to have a secured healthcare system with timely assist [1]. It is also vital to monitor and predict the signal deviation. By this IoT employed physiological signal monitoring system user can enable and predict individual condition like heart attack, chronic fever, elder care and also support, preventive measure and wellness [2–4]. The quality of care can be improved reducing the patient travel problem, providing reliable assist when needed. The proposed IoT-based healthcare system employed deep learning algorithm with an intelligent sensor network to acquire a vital human physiological signal. The collected signal has shared a wireless medium to the central cloud server for analysis and visualization.

IoT is an assistive technology for transport, infrastructure development, traffic monitoring, *etc*. From this advantage, IoT makes connection with the signal in modern healthcare system [5]. In terms of healthcare system, it provides first connection [6] and improved quality of life [7]. Conceptual view of the proposed IoT-based healthcare system for accurate signal monitoring is shown in Figure 1. The primary focus of this work to implement deep learning for prediction. IoT is used for connecting sensor for acquiring continuous time series data and do data analysis in cloud-based.

The main contribution of the research paper is

- To go for an IoT-based signal acquiring system.
- To employ a deep learning model for prediction of physiological signal for data visualization and reliable assist from service provider.

In the work of [8] used home automation by connecting different components for controlling in a single application. But they have not used data visualization and signal controlling methods for system implementation.

In the work of [9], the author used a smart log system for nutrition estimation, but not used the signal analysis counterpart. They received a low average accuracy for body fat estimation. Machine learning techniques with r-peak detection are introduced by the work of [10]; in detecting the peak wave pattern, first the network is trained with a standard signal which is available as dataset of some measured data are considered as reference data. They used a perceptron model to train the network and with the learned weight and bias value the next set of signals is trained. Once the particular network is trained for the signal, the weight and bias are not changed due to the lack of flexibility in the learning algorithm.

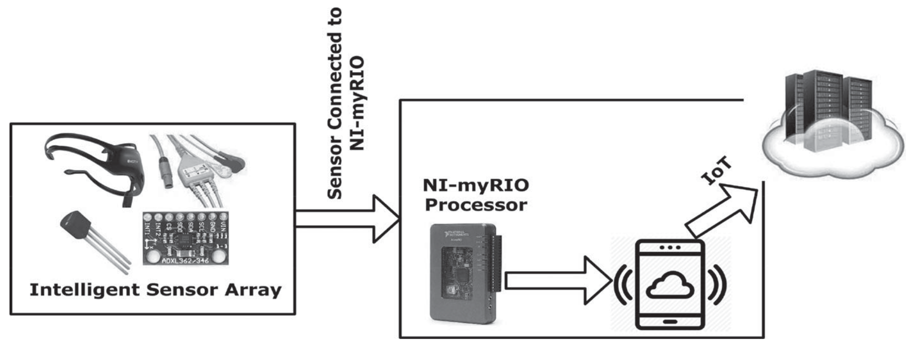

Figure 1: Proposed Smart-Monitor Signal Log system conceptual view

The remaining section of this research work is organized as follows: in Section 2, a comparative overview of various related work is given as background study. Section 3 explains the architecture of IoT-based signal monitoring system. Section 4 gives the data flow and prediction algorithm of the future signal by deep learning model. Section 5 gives the design of prototype model and experimental case study. Finally, the conclusion of research findings is summarized in Section 6.

2. RELATED WORK

Most of the research works in IoT application are multi-dimensional. Wireless remote health monitoring systems have been recommended by various researchers due to their high efficiency in delivering rigorous time-sensitive, accurate information to the patients. In 2017, Ahmad and Lina [11] first proposed a wireless Patients Adoption system for Integrated Model of Facilitators and Barriers. The system that comprised of a multi-layer architecture consists of sensors, web servers, and databases.

In the work of [12], the author used IoT application to transporting vehicular tracking and indication. But they followed a conventional communication medium with high power consumption and an energy management was introduced by the work of [13]. A wrist watch-type method to monitor pulse rate was proposed in the work of [14], but they have used a computational algorithm.

In the human activity analysis [15] and smart pill [16] some recent works used IoT, but they have not used the deep learning for data analysis in the cloud-based system. In this work, authors have used MEMS-based sensors which are in contact with the patient. Also, some preventive measures are necessary for using this conventional sensor. Since the complexity in the sensor formation, lack of signal conditioning element is the major problem faced by the experimental result.

Many researchers have worked towards IoT application to develop an accurate monitoring and corrective system in the work [17], a diet monitoring system developed by a visualizing system. This can be possible by IoT-connected monitoring unit by the frequency of user eating in an average day.

An automatic chewing system [18] was developed by the authors to identify the human activity and they have used a discontinuous measurement for acquiring signal and an offline computation was used. Also, they have used a neckband which consists of an array of electrode. This causes a signal measurement problem for the patient.

Hence this research work utilizes the advantage of various related works and contributes to design and developed an end-product as patient consumer electronics to improve timely assist and accurate prediction of physiological signal.

Hongxu and Niraj [19] proposed a framework for healthcare to provide reliable assist at home. This architecture mainly emphasized on data transmission between installed server serving closer to the edge at patient homes and remote hospitals. Daniele *et al.* [20] focused on the application of an advanced computing technique for classification of sensor data. They used the concept Deep Learning Approach to provide sensor data analytics from the Mobile or Wearable Devices. These devices act as data collection point in their work.

In recent years, many research works have proposed remote-assisted smart wireless real-time patient monitoring systems [21–29] but have not put importance on accurate, timely assist and measured parameter delay-related parameters during transmission.

Therefore, to handle health emergencies in real-time, an IoT-based healthcare system using deep learning algorithm is contributed ahead.

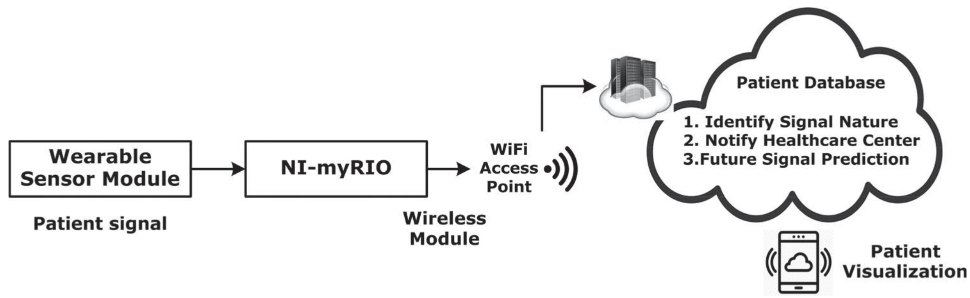

Figure 2: Architecture of proposed signal monitoring system using the Deep Learning Network

3. MATERIALS AND METHODS

3.1 Architecture of Proposed Patient Monitoring System

The architectural overview of the proposed deep learning employed physiological signal monitoring system is shown in Figure 2. The system includes an intelligent sensor for automatic continuous acquiring of physiological signal, wireless data transmission to the cloud server by the coordination of National Instruments myRIO processor with Wi-Fi module. NI-myRIO is capable of providing high-speed connection to all the things (intelligent sensor) connected to the signal monitoring system. The proposed learning architecture consists of the following four major modules.

(1) Monitoring Unit: An intelligent sensor array with myRIO processor.
(2) Processing Unit: myRIO wireless transmission using Wi-Fi module that was enabled.
(3) Visualization and Storage Unit: IoT gateway for data visualization for processing.
(4) Learning Unit: Signal feature prediction and notification module.

The real-time implementation of the proposed Smart-Monitor IoT framework using EEG, ECG, pulse rate, temperature, and pressure sensors is shown in Figure 3.

3.2 Monitoring Unit

The Monitoring Unit (MU) is realized as a sensor array. The main contribution of this research work was made possible by using an intelligent sensor to form a wearable sensor network for subject data measurement. Here, Emotive EEG sensor, BPL ECG Electrode, ADXL362 accelerometer sensor, and plug in type photoplethysmography (PPG) sensor are considered.

The emotiv EEG sensor is a high-speed wearable EEG signal pick up which is connected to the analog pin 1. It is an auto-correlated sensor with denoising DFT filtering approach. Hence a real-time signal assessment of possible by this precision sensor. For the measurement of ECG signal, BPL 12 channel ECG sensor module for measurement was used. This sensor was connected in analog input pin 2 to acquire continuously, whenever the assist is needed for signal analysis.

The next onboard sensor is to monitor temperature continuously. For this MAXIM a very high accuracy of 0.05°C from 24°C to 38°C was used. It is a 24-bit resolution and very low consumption. It can provide high-temperature peak detection for the different positions placed; it can provide an accurate value by the compatible 2-wire serial interface. To monitor the patient heartbeat, a PPG sensor was used. This sensor is plug-in plug-out type. For continuous monitoring of the subjected patient heart beat it consists of an analog processor APDS-9008 with high gain amplifier. This isolate signal from noise incurred during the formation BSN. By this configuration, heart beat at fingertip can be measured. Hence, the patient daily activity is not affected.

3.3 Transmission and Data Visualization Module

To assist a high-speed measured signal transmission, all the intelligent sensors are connected to NI myRIO form with a Wi-Fi module of high-speed data transmission. It uses a Xilinx FPGA programmable processor which consumes very low power. This myRIO processor is very much suitable for signal transmission and receiving.

It has a power consumption of 16.5 mA during the signal acquired by the user. For data visualization by the patient EVOTHINGS applications have been used. The NI-myRIO module is communicated to Evothings app. This application can also enable us to use a web-based application. This application can be deployed on smart phone with android OS and iOS platforms. By this application the patient, service provider can monitor the patient's vital physiological signal continuously. The

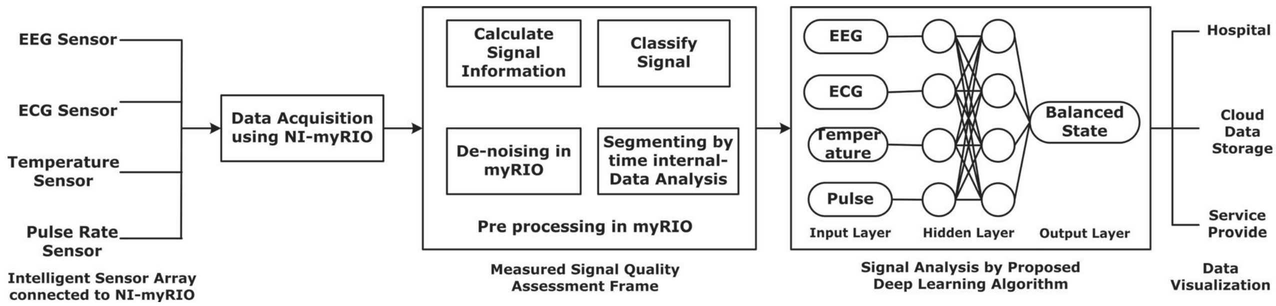

Figure 3: Overall IoT-based Smart-Monitor Signal Log system interconnection for classification based on extracted feature for a user

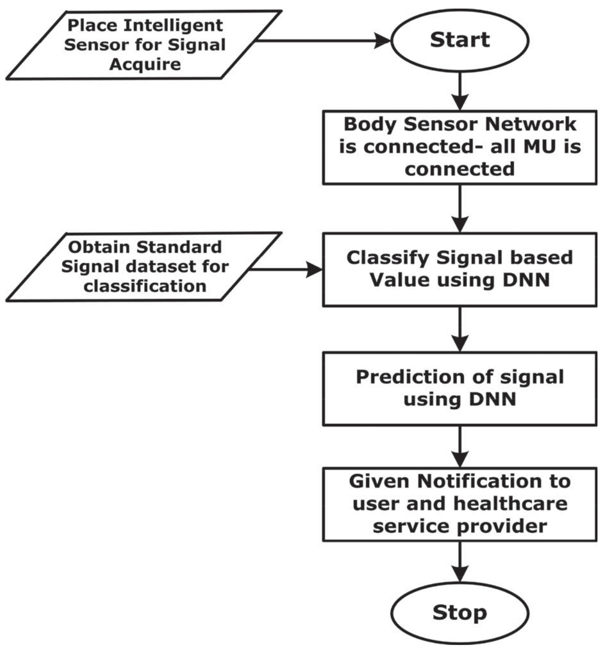

Figure 4: Data flow in the proposed Smart-Monitor Signal Log system

overall integration of Smart-Monitor system with signal analysis task is shown in Figure 3. Figure 3 shows a full architecture of Smart-Monitor with output classification from the sensors.

The measured signal and the signal future prediction are visualized by the user smart phone also. The signal monitoring data flow is presented in Figure 4. In the data flow we have indicated the logging time stamp to determine the average signal processed by the monitoring unit. With this signal quality-aware computing in IoT architecture, we can identify signal misclassification.

4. PROPOSED DEEP LEARNING MODEL FOR SIGNAL CLASSIFICATION

For learning the acquired patient physiological signal and to classify in cloud-based IoT system, we have proposed a Deep Neural Network (DNN) to extract features of the acquired signal in the sensor array. Based on training with standard signal a DNN structure is used by the score-search approach. In this approach, we compute a scoring function to search for constraint-based signal.

Consider the probability distribution of a two-signal counterpart. The signal measured by BSN and standard data value are given by Bayesian theorem equation 1;

$$P(M|N) = \frac{P(M \cap N)}{P(N)} \text{for } P(N) \neq 0 \tag{1}$$

This probability value is considered as weight update. The factor connects these two factors in a likelihood ratio. Hence, we have considered a three-layer back propagation model from Equation (1). The weight connection of input–output layer for internal activity is obtained by Equation (2).

$$Y_i = \sum_{i=1}^{n} W_{ij} X_j \tag{2}$$

where W_{ij} is the weight associated to the connection node, X_i represents weight, and Y_j is the total weight for final output. The activation function for total processed output is given by $Y_{net} = f(Y_i)$. The maxpooling in the proposed structure is given by Equation (3). This gives the new weight value and actual output.

$$Y(n+1) = Y(n) + \eta[t - y(n)] * X_i(n) \tag{3}$$

To train this DNN for determining abnormality for the acquired signal, a stochastic descent method was used.

The algorithm for learning the signal acquired is given in Algorithm 1. In this method a standard value is searched by gradient at each point. This method has the advantage such as to predict a new acquired signal. Figure 5 shows the implementation of the proposed algorithm using a Deep learning model. In Figure 5, we have shown the number of input layer sensors with the hidden layer function.

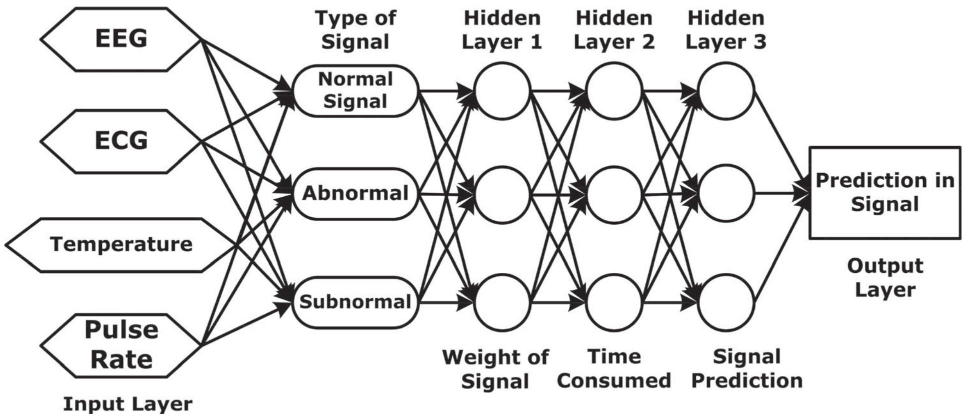

Figure 5: Proposed DCNN learning model for Signal Log in Smart-Monitor

After acquiring a different measured signal, categories have been constructed by a three-layer back propagation learning rule. We have adopted criteria as the first layer is linear separable, the second layer is fully connected, and the third layer that is presented by linear activation function was considered for building the deep learning model. Features like time of acquiring, magnitude of signal were measured. This makes the proposed learning model to develop an IoT-based signal monitoring system.

Algorithm 1: Signal learning algorithm for the proposed DNN using the stochastic Descent method

Input:	Begin the sensor monitoring using EEG, ECG, Temperature, pulse rate
Initialize	Weight, number of hidden layer convolution and max pooling
1:	While not converged do
2:	for input I = 1 to n
3:	Signal feed forward: compute Y output to each layer
4:	Back propagation of error: update Network and bias b
5:	Compute gradient
6:	Calculate output Y using equation 3
7:	end for
8:	end while
9:	return trained network output

5. EXPERIMENTAL SETUP OF THE PROPOSED SYSTEM

In this work a prototype consumer electronic product by implementing into two connected phases was designed and developed. Physiological signal acquisition and analysis of the signal were acquired.

5.1 Physiological Signal Acquisition for the Signal Log System

Signal acquisition involves the hardware design of the physiological sensor system. This was implemented with the help of commercial sensor components, as described in Section 3.2. The main parameters which have been taken for the design of such system are reliability, hand-held appearance for the patient for monitoring. For this commercial component the sensitivity and accuracy are specified by the manufacturer.

For the proposed Signal Log system, physiological signals like EEG, ECG, temperature, and pulse rate as some notable signals are considered to acquired and formed sensor system. The output of sensor array system is connected to NI-myRIO for data retrieval. The architecture of NI-myRIO consists of on chip Field Programmable Gate Array (FPGA) high frequency oscillator, regulated supply.

As per our proposed design the output remains high when serial data output and serial clock is ready. While designing the Smart Log system, the average accuracy of signal measured is calculated based on user compatibility and usage factor like power consumption of high processing of signal, portability. For this purpose, NI- myRIO with inbuilt Wi-Fi module was used. For validation of the proposed model, we considered an existing model [19] and compared the characteristic. Table 1 gives the comparison of two-signal logging system. From Table 1, it was identified that, our proposed model of transmitting acquired patient physiological signal to cloud, by bringing the connected “Things(sensor)” as IoT-based System design is made possible in an efficient way.

5.2 Laboratory Prototype Model of Signal Log System Design

The proposed Smart-Monitor system is used to acquire and monitor the physiological signal by patient and for accurate prediction. For this objective we need a highly sophisticated data analysis environment [20]. Hence, in

Table 1: Characteristic performance comparison of the proposed Smart-Monitor system and other conventional systems

Specification	Debajyoti *et al.* [22]	Sumit *et al.* [10]	Proposed Smart-Monitor System
Sensor	Temperature, heart beat	ECG	EEG, ECG, temperature, pulse rate
Power consumption	Depend on operation > 10 mW	3.9 mW	1.5 mW
User interface	PC	PC	PC/Smart Phone
Wireless connectivity	Cc32750, 3 GHz	RFID	WIFI
Classifier process	BPL	R Tool	WEKA
Learning model used	–	Bayesian Network	Deep Learning Network
Data analysis tool used	Atmel Processor	Arduino Processor	NI-myRIO Processor

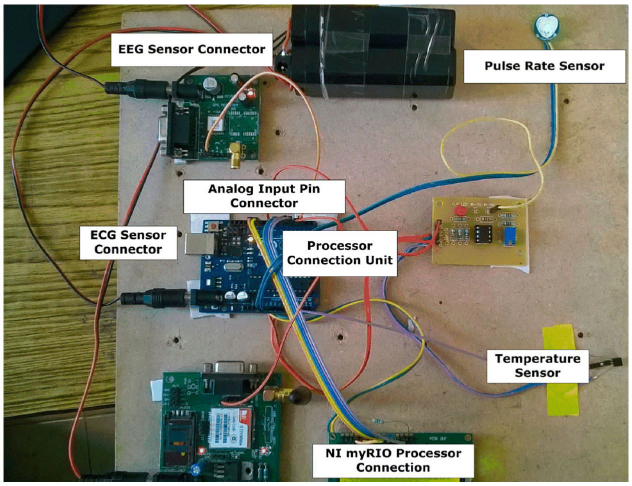

Figure 6: Photograph of prototype Smart-Monitor Signal Log system setup

Table 2: Hardware specification comparison of the existing model with the proposed Smart-Monitor Signal Log system

Characteristic	Proposed Smart Log system	Conventional Smart Log system
Processor clock speed	96 MHz	24 MHz
WIFI module	Built in with Processor	External module
Input/output Pin	64 PIN with dual channel	12 PIN
Physical dimension	40×20 mm^2	140×60 mm^2
Operating voltage	2–5 V	12 V
Transmission mode	Duplex	Simple
Accuracy (average)	97.5%	87.4%

Table 3: Experimental result comparison

	Learning algorithm used	Average accuracy	Computational time in seconds
Proposed Smart-Monitor System	Deep leaning model	97.2%	65
Sumit *et al.* [10]	Bayesian Network	88.45%	148

this work, Waikato Environment for Knowledge Analysis (WEKA) tool for classifying the acquired signal into various classes was used. NI-myRIO generates lvm (LabVIEW measurement file); this entry is passed to WEKA. The.lvm file used predictive modeling as input to the system. It contains 10 different patients acquired input by a Signal Log system. Figure 6 shows the photograph of laboratory prototype model developed. This model is implemented using shelf components.

5.3 Experimental Result

An overall compositional characteristic of existing Data Log and our proposed Smart-Monitor Signal Log system is given in Table 2. The performance of this research is obtained based on the accuracy of classification of EEG, ECG, Temperature and Pulse Rate. In the proposed classification system, the pattern analysis follows the physiological signal information measured. Evaluation of the proposed system is based on the average accuracy of signal prediction in comparison with the standard dataset signal. Using Algorithm 1 output classes like Normal, Abnormal, subnormal were predicted. Using Deep CNN, this classification was completed, by taking seven attributes from the acquired signal. For the considered prototype model to extract EEG, ECG, temperature profile, and pulse rate, an average accuracy of 97.5% was obtained.

In this research work, four sample signals were considered as input for the proposed deep convolutional neural network (DCNN). Seventy-five percent of data are considered as dataset for training (Learning phase) and 25% of data are used for testing phase (prediction phase).

In all the cases an average accuracy was obtained of 97.2% as the worst case. Hence, this system is very much suitable for prototyping an IoT-based physiological modeling system. The outcome of this paper can be a smart consumer electronics for patient monitoring.

Table 3 summarizes the result comparison of conventional data monitoring system with our proposed physiological signal model. From the comparison of results, it is identified that the proposed Deep learning method outperforms other conventional existing learning methods based on the Bayesian Network approaches. As compared with the signal monitoring system of existing approaches, the prototyped model is quite simple with a high accuracy of 97.2% with reduced computation time of 65 s, whereas the conventional method has 88.45% with a high computation time of 148 s for ECG signal in real-time monitoring environment.

6. CONCLUSION

In this work, an automatic physiological signal monitoring Smart-Monitor system is presented. The designed prototype model is a consumer electronics low cost, high accurate system. A deep learning algorithm was developed for the acquired signal feature extraction and signal abnormalities by analysis using WEKA. To increase classification accuracy, data analysis for continuous acquiring input dataset was used. By this signal analysis, the suggestion provided to the patient to meet healthcare service provider was also addressed. Hence, this system can use as a consumer product for sick aged patient and also for household. For the considered prototype model to extract EEG, ECG, temperature profile, and pulse rate, an average accuracy of 97.5% with a computational time of 65 s was obtained. Hence, this proposed Smart-Monitor Signal Log system can be used as an integrated product to accurate prediction and keep track of daily activities.

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