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Smart Cardiac Care: Leveraging IoT, Healthcare 4.0, and Fiber Bragg Grating Sensors with Machine Learning Algorithms

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Abstract: Recent developments in home-based monitoring, telerehabilitation, mobile health, and other aspects of the healthcare industry have led to the digitalization of cardiac parameter monitoring; including Heart Rate Variability (HRV) analysis. The Internet of Medical Things (IoMT) technology in conjunction with different sensors presents an acceptable solution towards the above advancements. Fiber Bragg grating (FBG) optical sensors are perfect for continuous cardiac monitoring if combined with machine learning (ML).The main goal of the study is to detect heart forces and vibrations in real time, which will result in the development of a novel FBG sensor. This sensitive sensor has been developed especially for the best possible detection of heart vibrations using PDMS polymer. Digital Signal Processing techniques enable the measurement of the mean Standard Deviation of Normal to the Normal intervals (SDNN), Heart Rate (HR) and the Root Mean Square of Successive Differences (RMSSD), apart from Body Temperature. The work also discusses about an IoMT-based recommendation system using HRV and statistical parameters to compare different models of ML such as RBF, PLSR, RF, FNN and DNN. The Random Forest algorithm's high precision is demonstrated by its values for R-squared error (1.000) and RMSE (0.5763). Finally, the study concludes with a comprehensive approach to cardiac monitoring and the early diagnosis of heart disease in healthcare settings using the Decision Support System (DSS) in conjunction with IoMT.

Keywords: *Remote cardiac parameter monitoring, HRV, IoMT, FBG sensors, ML, PDMS polymer, SDNN, HR, RMSSD, RMSE, R-squared error, DSS.*

1. Introduction:

Over the last few years, healthcare has observed the welcoming of spectacular technologies such as FBG sensors, HRV analysis, IoMT, and ML, which are revolutionizing patient care [1]. To address our increasing requirements, this convergence is very productive, especially in the development of sensors. Of these, the most innovative is Fiber Bragg Grating (FBG) sensors which have found a place in health care fields [2]. Such sensors are of small dimensions, affordable, high-speed, and immune to hostile conditions and are applied in exhaustive fields, such as biomedical systems and structural assessment [2]. In the sphere of medicine, with Cardio Vascular disease (CVD) being the leading cause of death worldwide, the potential health and vital signs indices, including HRV analysis, need to be under control [3]. HRV parameters are highly valuable for diagnosing and assessing autonomic nervous system function, aiding in the diagnosis of cardiac-related diseases [3, 4]. Unlike standard electrical devices that need to be carefully protected, FBG-based sensors have the potential to be employed in both invasive and non-invasive applications. They can also function reliably in adverse conditions, including MRI settings. These sensors operate optimally in high electromagnetic noise and thus have the possibility of improving the patient’s care in a number of healthcare facilities [5].

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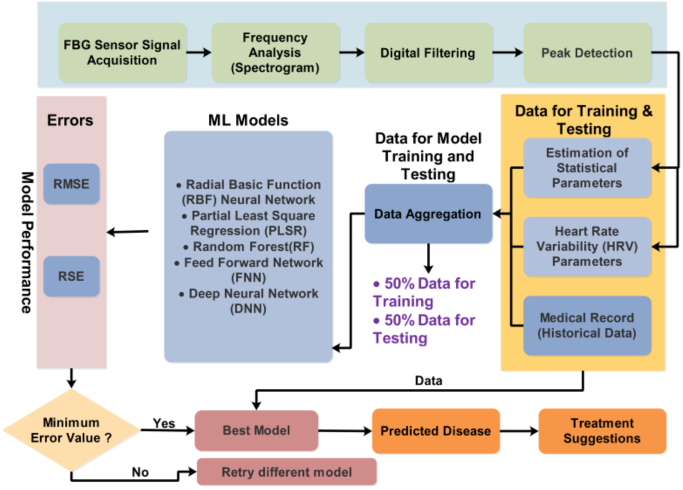

Figure 1: Block diagram of proposed IOMT-based Cardiac monitoring System with FBG sensor

Among the types of optical sensors, FBG sensors are applicable for the healthcare monitoring since they do not cease functioning due to electromagnetic interference. Cardiac and respiratory sensors have especially been described to benefit from these sensors. For real-time monitoring, it is therefore imperative to connect IoT, polymer engineering, Data Analytics, DSP, and DSS [5]. Real-time data acquisition and consecutive long-term FBG based biocompatible sensors monitoring is possible due to the integration of the designed system and ML methods are utilized for the detection of anomalies and heart conditions. DSS also helps to improve the decision making as is shown in Figure 1. The change of paradigm that the application of FBG sensors offers the improvement of healthcare infrastructure as it gives solutions in a complex environment.FBG sensors are used in various fields of structural health monitoring in buildings, aircraft structures, gas pipelines and railway tracks among others. In the biomedical area FBG sensors are constantly incorporated in the wearable devices for the physiological signals where they perform the role of sensing the HR and RR. For instance, Tavares et al. presented an efficient but adaptable material with FBG sensor intended for chest monitoring in the work carried out in 2022, which offered substantial correlation coefficients for RR and HR and conventional reference instruments [6]. In a comparable observational accuracy of RR and HR using FBG sensors, the study by Ogawa et al. (2019) [7], the researchers obtained similar findings. Further, M. Krej et al. (2019) used the machine learning for the analysis of plethysmography with the FBG sensors and the research study yielded favorable outcome [8]. Similarly, Nedoma et al. (2018) investigated the use of bandpass filters to accurately measure RR and HR on the chest using biocompatible PDMS in conjunction with FOI and FBG probes [9]. There are works by Zhu et al. (2014), Dziuda et al. and Elsarnagawy (2015) whereby FBG sensors were incorporated into textiles, sheets, and mattresses for HR and RR monitoring. Therefore, the future studies for these technologies need to focus on clinical trials, procedure practicality, and permanency. Table 1 presents findings on FBG optical sensors in cardiac healthcare monitoring.

Table 1: FBG Optical Sensors Literature Review

Sl.No.	Articles	Research Findings	Research Gaps
1	Tavares et al. (2022)	Flexible FBG sensor with a bandpass filter for RR and HR monitoring.	Variation in Sensor sensitivity.
2	Ogawa et al. (2019)	Array of FBG sensor on brachial artery, filters.	Evaluation of Signal Processing Models.
3	Krej et al. (2019)	FBG on acrylic glass plate, RMSE 1.48.	Adaptation to Frequency Range.

		.	
4	Nedoma et al. (2018)	PDMS- based FOI and FBG probes, Median filters. .	Age range and specific error data not specified.
5	Zhu et al. (2014)	Arrays of FBG sensors on mat, filters, HR.	Multi-FBG approach for signal reliability.

This article introduces an intelligent real-time healthcare tracking system, structured in six sections to enhance clarity and coherence. The first section provides an introduction of the optical Fiber Bragg grating (FBG) sensor and highlights a comprehensive review of relevant prior research, highlighting its applications and advantages in cardiac monitoring. In Section 2, we outline the research objectives of the smart healthcare system. Section 3 emphasizes on working principles, design considerations and experimentation of the FBG sensor. Section 4 sheds light on disease identification using machine learning. Section 5 presents the results of the experiments and subsequent discussions. Section 6 summarizes conclusion and future work of the study. Finally, the reference section lists all of the papers referenced in this paper, giving readers access to other resources for subsequent research.

2. Research Objectives and Motivations

- **Objectives:** The proposed IoMT system using FBG sensors aims at devising the distributed cardiac monitoring facility having following several research objectives:

➢ Objective 1: Develop FBG sensor element capable of recording BCG signal in real-time and make them compact, non-toxic, biocompatible and plug-and-play with the health care systems.

➢ Objective 2: Develop a Digital Signal Processing (DSP) system for noise removal and assessment of mean HR, Standard Deviation of Normal to Normal Inter beat Interval (SDNN), percent Normal to Normal Interval (pNN50), and the Square Root of the Mean Squared Differences (RMSSD).

➢ Objective 3: Develop a framework of the Decision Support System (DSS) to extract crucial alerts in medical emergencies; and also, manage varying cardiovascular data and timely alert generation.

➢ Objective 4: In experimental assessment test the IoMT based Cardiac Monitoring System and its accuracy, validity, sensitivity, and ability to deliver alerts and early identification of heart diseases in actual time healthcare environment.

- **Motivation:**

➢ **Real-time BCG Signal Capture:**

Miniaturization: Makes sure that the sensors which are worn for an extended period do not pose an inconvenience to the human body.

Biocompatibility: Assures that the sensors do not pose any harm of giving negative effects when in consistent touch with the body.

Seamless Integration: This makes them easy to integrate into already existing health care systems, thus enhancing their use and improving on patient care.

➢ **DSP Model Development:**

Noise Reduction: Helps in refining the cardiac measurements by minimizing noise.

Accurate Parameter Estimation: Delivers accurate assessment of critical parameters of cardiac function (HR, SDNN, pNN50, RMSSD) that are vital for cardiac health assessment**.**

➢ **Decision Support System Design:**

Complex Data Handling: Enhances the complex processing of cardiac information, and therefore raises accuracy of different diagnosis and management in clinical practice.

Effective Alert Generation: Guarantees that a person is notified when a medical emergency is likely to happen hence offering a chance of saving lives.

- **System Testing and Validation:**

Precision and Validity: Ensures that the system is correct and is well trusted to help in the special need of health monitoring.

Sensitivity and Effectiveness: Illustrates how it alerts and identifies early signs of heart diseases long before it happens thus promoting preventative care services.

3. Working principle, Design and Experimentation

Recent optical sensing systems rely on FBG sensors that function by interacting with periodic changes in the refractive index of the fiber structure [13]. With the reflected wavelength, or Bragg wavelength, closely linked to the period of the grating and variations in refractive index, this periodicity serves as an effective wavelength filter which is represented in Figure 2.A unique, narrow-band Bragg wavelength is generated when broadband light contacts the grating under the Bragg condition. Modifications in the grating pitch and refractive index have a direct impact on variations in the Bragg wavelength [13]. Peak Bragg wavelength is defined by Equation 1 in the context of coupled-mode theory.

$$\lambda\_B = 2\eta\_eff\ \Lambda \quad (1)$$

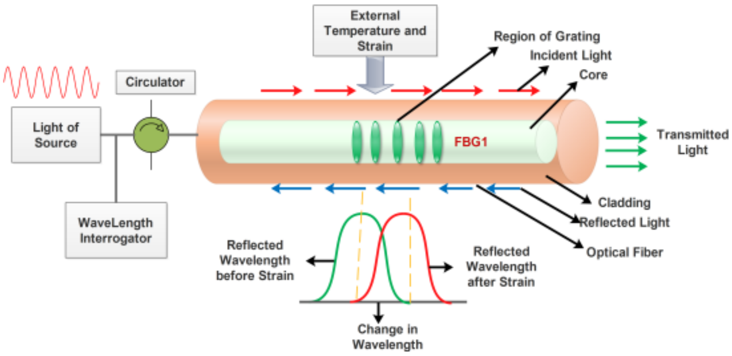

Figure 2: Working Principle of FBG Senor

In addition, Equation 2 demonstrates how changes in temperature and strain affect the peak Bragg wavelength.

$$\frac{\Delta\lambda_B}{\lambda_B} = \left(\frac{1}{\Lambda}\frac{\partial\Lambda}{\partial\varepsilon} + \frac{1}{\eta_{eff}}\frac{\partial\eta_{eff}}{\partial\varepsilon}\right)\Delta\varepsilon + \left(\frac{1}{\Lambda}\frac{\partial\Lambda}{\partial T} + \frac{1}{\eta_{eff}}\frac{\partial\eta_{eff}}{\partial T}\right)\Delta T \quad (2)$$

These equations can be employed by scientists and engineers to develop precise and effective FBG sensors for a variety of applications such as cardiac monitoring and other applications [14].

The study employs the phase mask technique to fabricate FBG sensors by directing UV light onto an optical fiber to form a Bragg grating structure [14]. This grating serves as the sensing element for strain and temperature, with the potential to incorporate multiple gratings on a single fiber for concurrent parameter measurement [14, 15]. The FBG is embedded in a polymer layer through a meticulous curing process, and design parameters for sensitivity are optimized using Finite Element Analysis in COMSOL Multiphysics [15, 16]. This optimization improves the sensor's reliability and performance in practical applications. Proper installation of the FBG sensing element, embedded in PDMS, within a wearable chest belt positioned over the thoracic region is essential for effective real-time monitoring of cardiac vibrations.

In a laboratory environment, FBG sensor embedded in PDMS was designed. Heartbeat patterns could be captured with the use of an Ibsen IMON 512 FBG interrogator, an Ibsen SLED light source that operated at 1550 nm, and a PC equipped with an Intel Core i5 6th generation processor, 8 GB RAM, and a 512 GB SSD. A Gigabit switch was used to connect the PC and FBG interrogator. LabVIEW application uses a specific DLL library to handle data collecting. This method focuses on sensing cardiac stress using wearable chest belts with integrated FBG sensors and associating variations in the FBG period to cardiac events, including arrhythmia and normal. With an accuracy of 1 pm, sampling the FBG at 1000 Hz in the wavelength range of 1550–1560 nm ensures accurate cardiac dynamics monitoring regardless of the presence of possible interference. Figure 3 illustrates the configuration.

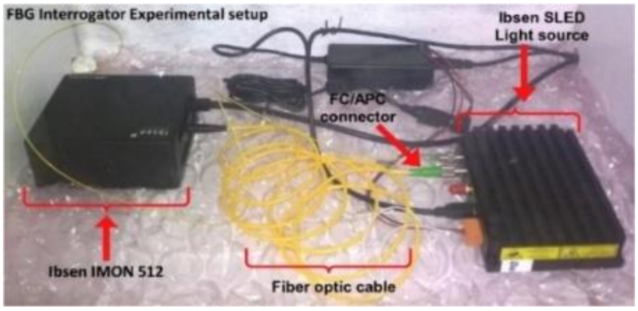

Figure 3: FBG Interrogator Experimental setup

4. Disease Identification using Machine Learning

Heart rate variability (HRV) aspects and statistical features have been tracked by various kinds of machine learning algorithms that are essential for early cardiac disease prediction. Some these models are:

➢ Radial Basis Function Neural Network (RBF): This type of neural network analyzes intricate, non-linear trends in cardiac data by using Gaussian radial basis functions.

➢ Partial Least Squares Regression (PLSR): one can determine common variance between predictors and response variables and address multicollinearity.

➢ Random Forest (RF): Enhances predictive ability by integrating several decision trees, boosting accuracy.

➢ Deep Neural Network (DNN): Provides deep understanding into heart health by automatically learning and extracting representations from unprocessed data.

➢ Feedforward Neural Network (FNN): Using input, hidden, and output layers, a Feedforward Neural Network (FNN) can help with tasks like pattern recognition, regression, and classification.

To provide effective cardiac disease diagnosis and classification, each of these models incorporates statistical factors, and HRV analysis parameters. Their different approaches demonstrate the adaptability and efficiency of machine learning for improving cardiac health monitoring.

5. Results and Discussions

Two participants in different heart states had their real-time cardiac signals recorded by the FBG-based sensor. However, motion disturbances and surrounding noise could easily interfere with the signals, resulting in overlaid baseline noise. The two subjects' raw signals are shown in Figures 4 and 5.

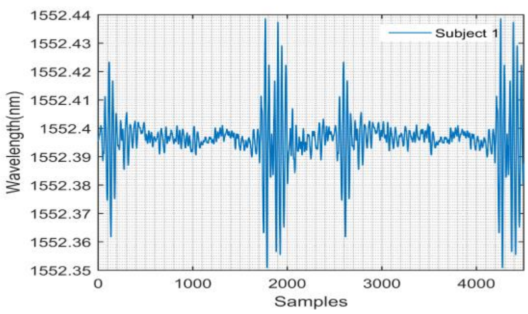

Figure 4: Cardiac Raw signal captured by subject 1

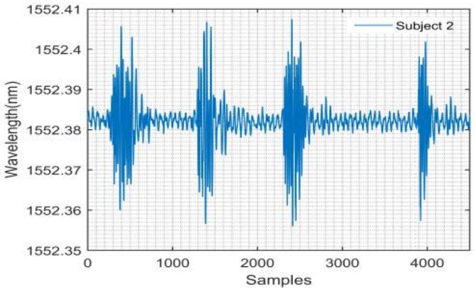

Figure 5: Cardiac Raw signal captured by subject 2

By analyzing changes in frequency over time, spectrograms assist in recognizing patterns and lower signal noise. Noise frequencies can be precisely determined using the Fast Fourier Transform (FFT), as subjects 1 and 2's Figures 6 and 7 illustrate. A moving average filter is used to smooth the original FBG signal. By averaging neighboring data points, it lowers high-frequency noise and sudden swings. Additionally, undesired low- and high-frequency components are removed while maintaining the critical cardiac frequency range using a uniquely developed Infinite Impulse Response (IIR) bandpass filter. These filters successfully attenuate or eliminate noise frequencies, as seen in Figures 8 and 9.

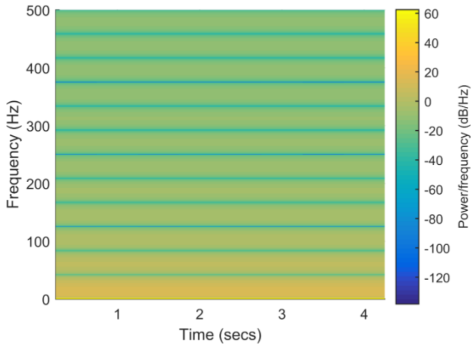

Figure 6: Subject 1 Spectrogram

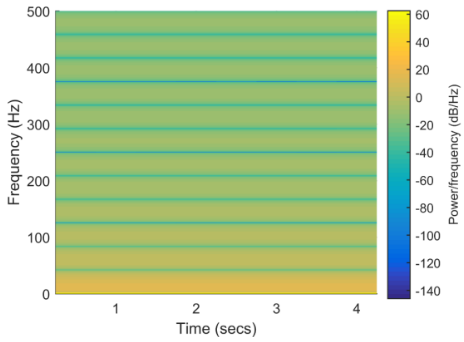

Figure 7: Subject 2 Spectrogram

With a sampling frequency of 1 kHz, the parameters to generate an Infinite Impulse Response (IIR) bandpass filter are set with a PassBand frequency of 10.0 Hz and a StopBand frequency of 140.0 Hz. It has 1.5 dB StopBand attenuation and a 1 dB PassBand ripple. In order to optimize the filter's efficiency in signal processing tasks, specific features are essential.

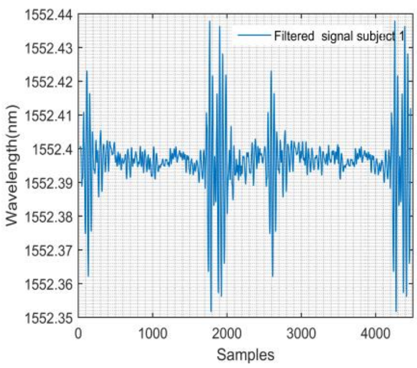

Figure 8: Filtered Cardiac signal captured by subject 1

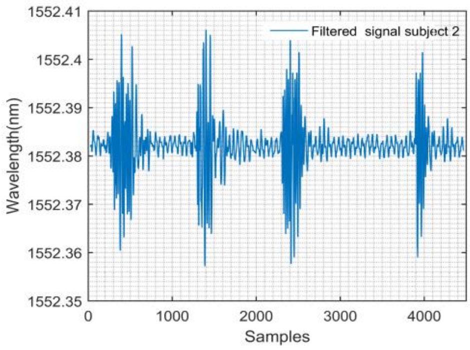

Figure 9: Filtered Cardiac signal captured by subject 2

Group delay is a measure of the time it takes for different frequency elements of a signal to pass through a filter. It correlates with the phase response of a filter. This idea is essential to signal filtering since it illustrates the way group delay changes with frequency and can cause signal distortion, especially for complex signals. Group delay should be considered into thought while selecting noise reduction filters in order to maintain the temporal details of the signal.

A relevant peak detection approach becomes required after the filtration phase. The output of the FBG sensor includes peaks that can be precisely recognized as individual heartbeats within the wavelength range of 1545.7 to 1545.9 nm. Locating and analyzing these identified peaks is essential for assessing HRV metrics such as HR, SDNN, and RMSSD. The graphic representations of the peaks derived from the filtered FBG signal are shown in Figures 10 and 11.

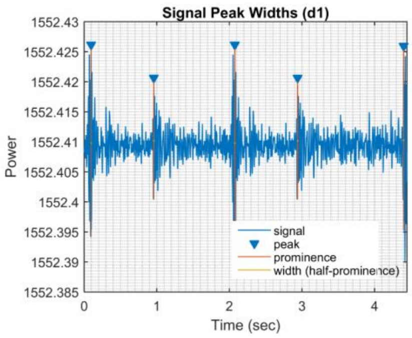

Figure 10: Peak of Subject 1

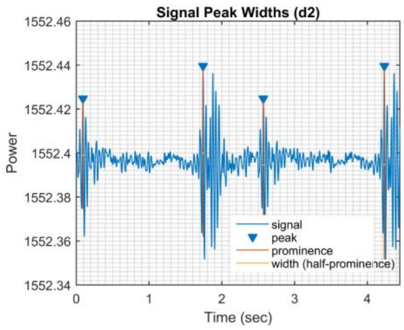

Figure 11: Peak of Subject 2

Table 2 presents HRV parameters for the experimental study subjects, including HR, SDNN, RMSSD, and pNN50. To further improve the study, Table 3 presents the participants' health statuses as well as statistical indicators like Mean, Sigma of the signal, Maximum Height, and Minimum Height.

The person aged between 30 and 65 has HRV parameters such as HR ranges from 55 bpm to 105 bpm, the root mean square of successive differences (RMSSD) ranges from 11.7 ms to 42.9 ms, while the standard deviation of NN intervals (SDNN) ranges from 20.4 ms to 51.4 ms. pNN50 count also varies from 3% to 23%. The values shown indicate the heart function that people in this age range typically have.

Table 2: Different Heart rate variability Characteristics of subjects involved in the experiment

Subjects	HRV parameters recorded by FBG Sensor				HRV parameters recorded by Standard HRV monitor				Error in Percentage			
	HR (bps)	SDNN (ms)	RMSSD (ms)	pNN 50	HR (bps	SDNN	RMSSD (ms)	pNN 50	HR (bp	SDNN (ms)	RMSSD	pNN 50

				(%)	**)**	**(ms)**		**(%)**	**s)**		**(ms)**	**(%)**
1	50.09	20.00	10.02	3	52.5 9	23.32	10.62	3.15	4.7	5.6	5.6	4.7
2	58.53	28.28	24.40	9	61.9 3	29.97	26.10	9.63	5.6	5.6	6.5	6.5

The maximum and minimum wavelength shifts are represented as Δ_mxh and Δ_mnh respectively. The wavelength difference from the FBG sensor's base wavelength (λ_B) is used to compute these shifts. Equations 11 and 12 give the mathematical representations of these notations.

$$\Delta_{mxh} = \lambda_{max} - \lambda_B \quad (3)$$

$$\Delta_{mnh} = \lambda_{min} - \lambda_B \quad (4)$$

Where λ_max is the peak wavelength in the FBG signal after filtering

and λ_mnx is the minimum wavelength in the FBG signal after the filtering.

Table 3: Different Statistical Parameters of Cardiac Signal

Subjects	**Age**	**Sex**	**Δ_mxh (nm)**	**Δ_mnh (nm)**	**Mean (nm)**	**Sigma**	**Subject Health Status**
1	42	M	1552.4061	1552.3572	1552.3820	0.0051	Arrhythmias
2	52	F	1552.4065	1552.2678	1552.3317	0.0137	Normal Person

In cardiac dynamics, a variety of models are employed for anomaly detection and pattern extraction, and these models are evaluated using RMS and R2 error metrics. Higher R^2 values show better signal variance capture, and lower RMS values indicate effective preprocessing. For robust training and testing, the dataset has been divided up. The RBF, or Radial Basic Function Neural Network, regularly achieves high R^2 (0.996-0.999) and low RMSE (0.000279-0.000283). The FeedForward Neural Network has poor performance, while Partial Least Square Regression (PLSR) performs moderately. Random Forest obtains a perfect R2 (1.000) even with a larger RMSE (0.5763). As seen in Tables 4, the Deep Neural Network operates moderately with room for improvement.

Table 4: Evaluation of Machine Learning Models

Models	**Training Data Set**		**Testing Data Set**	
	RMSE	**R-squared**	**RMSE**	**R-squared**
RBF (Product of two sigmoid)	0.000281	0.999	0.000272	0.999
RBF (Gaussian combination)	0.000283	0.998	0.000274	0.996
RBF (Generalized bell-shaped)	0.000282	0.997	0.000273	0.997

RBF (Spline-based pi-shaped)	0.000281	0.999	0.000272	0.998
RBF (Difference between two)	0.000279	0.997	0.000269	0.996
RBF (Sigmoid-based)	0.000281	0.996	0.000271	0.997
RBF (Spline-based S-shaped)	0.000283	0.998	0.000275	0.999
RBF (Trapezoidal)	0.000282	0.998	0.000276	0.997
RBF (Triangular)	0.000281	0.999	0.000269	0.999
RBF (Spline-based Z-shaped)	0.000282	0.998	0.000272	0.997
PLSR	0.53851	0.911206	0.53859	0.911226
FeedForward NN	0.100000	0.389381	0.110000	0.389808
Random Forest	0.5763	1.000	0.5763	1.000
Deep Neural Network	0.5763	0.8527	0.5773	0.8517

Having the lowest RMSE (0.000279 to 0.000283) and highest R-squared (0.996 to 0.999), the Radial Basis Function Neural Network (RBF) performs better than the others. The performance of partial least square regression (PLSR) is mediocre, with an R-squared of 0.911206 and an RMSE of 0.53851. The Feedforward Neural Network works less well, shown by its lower R-squared (0.389381) and larger RMSE (0.1). The Random Forest (RF) model achieves a perfect R-squared of 1.000, while having a larger RMSE of 0.5763. The Deep Neural Network (DNN) has an R-squared of 0.8527 and an RMSE of 0.5763, representing moderate performance.

6. Conclusions

This work demonstrates the way to effectively combine machine learning with IoMT-based Fiber Bragg Grating (FBG) sensing technology. Finite Element Analysis is employed to enhance sensor design, and various machine learning models, such as Radial Basis Function (RBF) networks, Partial Least Squares Regression (PLSR), Feedforward Neural Networks (FNN), Deep Neural Networks (DNN), and Random Forest (RF), are utilized for forecasting disease in real-time cardiac signal processing. With an RMSE of 0.5763 and an ideal R-squared value of 1.000, the Random Forest model stands out among them, demonstrating its outstanding ability to evaluate cardiac dynamics and enable proactive medical interventions. Real-time monitoring of cardiovascular indicators has been made possible by the incorporation of IoMT with cloud computing, that advances remote surveillance and early disease identification. This work integrates FBG sensors, machine learning, and IoMT for complete remote cardiac monitoring, thereby providing a significant contribution to the digital transformation of healthcare. It brings emphasis to how decision support systems and IoMT integration can be employed to provide comprehensive monitoring and early disease detection.

With the goal to further enhance remote cardiac monitoring and early intervention capabilities, future study should focus on process optimization and streamlining, investigating cutting-edge AI-driven decision support systems, conducting durability studies, and improving signal processing algorithms. This adaptable approach transforms healthcare delivery while also enhancing access to care in remote places through the use of FBG sensors and IoMT technology. It reduces the burden on healthcare institutions, encourages inclusivity, and may even save lives by providing real-time data and recommendations.

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