International Journal of Data Science and Artificial Intelligence (IJDSAI)
Volume 02, Issue 01, January-February (2024)

RESEARCH ARTICLE

DEEP LEARNING BASED WEARABLE DEVICE FOR OLDER PEOPLE MONITORINGSYSTEM

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Abstract - Activity recognition (AR) systems for older people are common in residential health care settings such as hospitals and nursing homes, thus numerous methodologies and studies have been developed to improve the effectiveness of AR systems. However, developing sufficiently robust AR systems using sensor data obtained is a challenging task. In this paper, a novel Smart Belt (S-Belt) for Monitoring of elder people using IoT is a smartphone application that predicts a health monitor for elder people and then sends that status together with the health state and anticipated behaviour to the family. Initially, the sensors in the smart belt such as temperature sensor, heartbeat sensor, oxygen sensor, and glucometer are used to gather data from the elders. The details from the sensors will be preprocessed using Stationary wavelet Transformer (SWT) technique and then classified using Multihead-CNN. Then the classified result will be sent to the end users such as doctors and their relatives through a mobile application. The simulation finding shows proposed method performance was evaluated in terms of ACU, PRE, REC, and F1S. The S-Belt model achieves the overall accuracy of 99.64%. MHCNN network improves the accuracy range by 9.5%, 4.42%, and 0.8% better than DNN, RNN, and CNN respectively.

Keywords: *Older adults, Internet of Things, Stationary wavelet Transformer, Deep learning, Multihead-CNN.*

1. INTRODUCTION

Human Activity Recognition (HAR) has recently emerged as one of the most prominent research topics [1]. HAR identification is a crucial tool for tracking a person's dynamism. It may be done with ML algorithms [2]. It automatically recognizes and analyses human activities based on information received from numerous smartphone sensors and wearable devices, such as accelerometer, position, and a number of other environmental sensors [3,4]. When integrated with other technologies, such as IoT, it may be used in a range of applications, including healthcare, sports, and industrial [5]. The monitoring of older people's health is rapidly increasing as sensors and AI technology progress[6]. Furthermore, the entire population is aging extremely quickly, and there is an increased fall risk for senior individuals, linked to many serious conditions such as heart attack, strokeand so on [7].

The HAR system has become needed for healthcare, whether in a hospital or nursing home [8]. It is a challenging problem for many scholars throughout the world, and they are attempting to find a solution that will make the lives of older people safer. Most smart gadgets include built-in sensors that detect and recognize the body's actions [9]. As a result, these devices determine the movement percentage for all types of users at the end of the day. In recent years, numerous research has been conducted for HAR using ML and DL, but only a few focus on developing a framework for the HAR system for older people [10,11]. This study employed a particular sort of sensor in the wearable device to monitor the activity recognition system and detect human motions for healthcare, as well as identify the worst actions that might endanger the life of an elderly person using DL techniques.

The main contribution is followed as:

- In this paper, a S-Belt for Monitoring of elder people using IoT is a smartphone application that predicts a health monitor for elder people.
- Initially, the sensors in the smart belt such as temperature sensor, heartbeat sensor, oxygen sensor, and glucometer are used to gather data from the elders.
- The data from the sensors will be preprocessed using SWT technique and then classified using Multihead-CNN.
- Then the classified result will be sent to the end users such as doctors and their relatives through a mobile application.

As a result, the remainder of this work is organized as follows. Discuss literature review related to elder people recognition in section II. The S-Belt method is discussed in Section III and an experiment is conducted in Section IV to examine its viability. The conclusion of Section V is provided by an experimental result.

2. LITERATURE SURVEY

Cloud computing and sensors are two examples of smart technology that may be used to monitor people's actions and make their lives easier. As a result of this revolution in this field, several issues arose that needed to be addressed and cleaned up, such as HAR and detection. An overview of a few advanced methods for assessing the condition of the elder people in this section.

In [12] introduced a smart healthcare system for heart disease prediction is suggested, utilizing an ensemble DL network. Logit Boost is a meta-learning classifier that reduces bias and variance while simultaneously increasing the DL methodACU. When compared to existing cutting-edge technologies, the suggested strategy outperforms them with a 98.5% ACU in heart disease prediction.

In [13] suggested a SHH monitoring system that examines the patient's blood pressure and glucose levels at home and alerts the healthcare provider if an anomaly is detected. Use SVM classification algorithms to forecast the patient's diabetes and hypertension status. Afterwards evaluating all sorting strategies, the SVM was found to be the most ACU and hence utilized to train the models.

In [14] developed a DNN-based signal prediction and estimation technique. A smart monitor is a consumer gadget that has an intelligent sensor. A Smart-Monitor system was tested on two users by calculating the accuracies of physiological signal prediction. It was found that 97.2% of the results were accurate in the prototype experimental setup.

In [15] Innovative medical care for older people. It revolutionizes medical science by improving the quality of care for the elderly while incorporating ML algorithms. The usefulness of the SHC model in monitoring older adults was demonstrated through experiments on IoMT datasets. It obtains improved accuracy during validation, resulting in an accuracy of 0.918.

In [16] developed DeTrAs of DL-based Internet of Health Framework to assist Alzheimer patients. An emotion detection strategy based on CNNs and a natural language processing approach based on timestamp windows were developed. In comparison to other existing machine learning algorithms, the assessment of DeTrAs shows a nearly 10-to-20% gain in accuracy.

In [17] presented an ML-based fall detection system. The system detects falls by classifying specific behaviors as fall or non-fall activities, and it notifies the elderly person's caretaker in the case of an emergency. SVM and DT are used to identify falls based on calculated attributes. The system achieves up to 96% accuracy utilizing the decision tree method.

From the above literature, developed various elder people healthrecognition system for alerts medical personnel in real-time but they have some drawbacks such as a familial discord, difficulty forming and maintaining friendships, lack of guidance, and take more time to monitor elder people. To overcome the above drawbacks, a novel S-Belt method has been proposed for predicting the health recognition system for elder people.

3. S-BELT METHODOLOGY

In this paper, a novel Smart Belt (S-Belt) for monitoring of elder people using IoT is a smartphone application that predicts a health monitor for elder people and then sends that status together with the health state and anticipated behaviour to the family. Initially, the sensors in the smart belt such as temperature sensor, heartbeat sensor, oxygen sensor, and glucometer are used to gather data from the elders. The details from the sensors will be preprocessed using SWT technique and then classified using Multihead-CNN. Then the classified result will be sent to the end users such as doctors and their relatives through a mobile application. Figure 1 shows the architecture of S-Belt method.

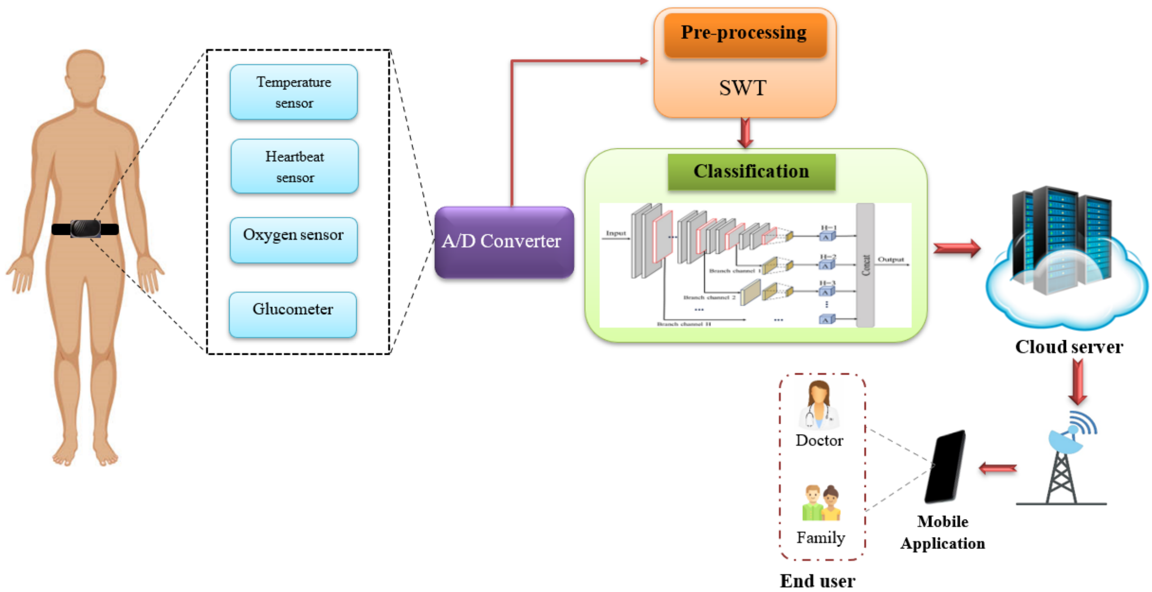

Figure 1. The overall workflow of proposed S-Belt

3.1. Data acquisition

In this stage consists of several sensors are attached to the wearable belt for predicting the state of the elders and the parameter like body temperature, respiration rate, movement, repetitive patterns. The wearable belt consists of temperature, heartbeat, oxygen level, and glucometer sensor. The temperature sensor sending out electrical signals to provide measurements. Sensors are made of two metals that generate an electrical voltage or resistance. Along with a rise in voltage, the temperature also rises. To determine acceleration, an accelerometer detects vibration. A magnetometer is used to determine the position relative to the north pole, and a gyroscope is used to measure angular movement. The A/D converter receives data from the device's built-in temperature sensor, heart rate sensor, oxygen level, and glucometer. A/D converter can translate analogy electrical signals for data processing method. Sensors are used for predicting the state of the child parameter is shown in Table 1.

Table 1. Various sensors and range used to predict the state of the elders

Parameter	Range	Sensors
Body temperature	35.8 °C to 36.9 °C	NTC sensor
Respiration rate	16 to 25 breaths per min	Piezoelectric sensor
Oxygen rate	97 to 100%	Oxygen sensor
Blood sugar level	90–150 mg/d	Glucometer
Heart rate	60–100 beats per minute	Heart beat sensor

3.2. Pre-processing using Stationary Wavelet Transform (SWT)

It is the process of eliminating unwanted high-frequency signals. SWT refers to the process of denoising a physiological signal. The wavelets can disclose features such as signal patterns, discontinuities, and noise. SWT is a modified wavelet transform. It can deconstruct time-invariant signals while preserving all of their information. It separates y-valued signals into approximation and detailed coefficient sets. The approximation and detailed coefficients may be calculated using equations 1 and 2, where I and j represent the number of stages of decomposition and position, and$cAP_{i,j}$ and $cDC_{i,j}$ respectively, stand for the approximation and detail coefficients.

$$cAP_{i,j} = \sum_{k=1}^{n} cAP_{i-1,j+2^{i}(n)} h(n) \tag{1}$$

$$cDC_{i,j} = \sum_{k=1}^{n} cDC_{i-1,j+2^{i}(n)} f(n) \tag{2}$$

The signal was then separated into frequency resolutions and subjected to gentle thresholding. Thresholding separates noise from signal. Following the ISWT, the decomposed signal was rebuilt using the inverse stationary wavelet transform. The denoised data is created using ISWT.

3.3. Classification via Multihead-CNN

Multi-head convolution is a CNN in which each time series is handled by a distinct convolution, known as a convolutional head. The architecture of MHCNN is displayed in Fig.2. Multi-head CNNs employ one-dimensional convolutions, where the dimension determines how the input data is processed. They are entrusted for extracting relevant information from sensor data. Sensors installed on machines in many industrial applications are unconnected and hence uncorrelated. They frequently form part of a heterogeneous sensor system, which allows them to gather data of multiple kinds, real-value scales, and even frequencies.

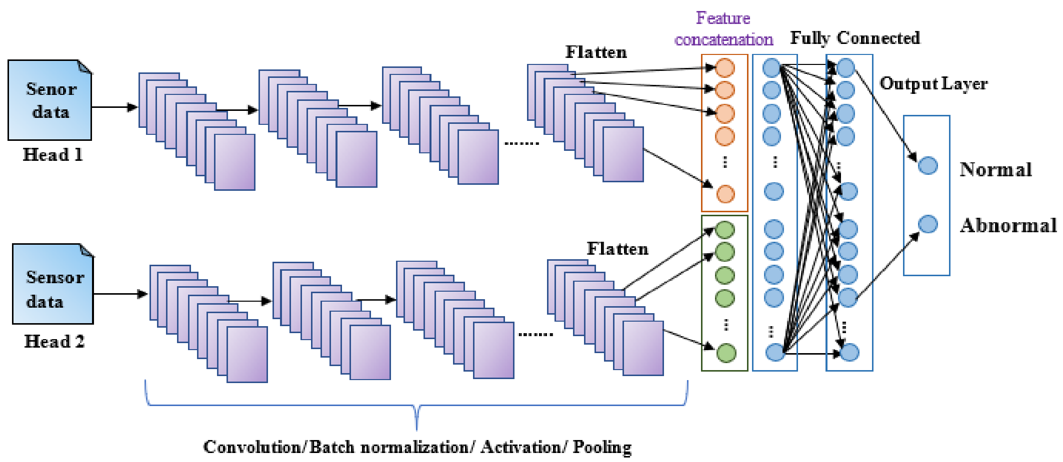

Figure 2. Architecture of MHCNN

The design suggested processes the time series using a sliding window rather than the entire sequence at once. A single time series can often represent many behaviors, particularly in industrial systems where an action is separated into phases. A convolution can be defined as follows,

$$y = \sum_{i=1}^{P} \sum_{j=1}^{Q} x(i,j) f(i,j) \tag{3}$$

Where y is the output from $x(i,j)$ and the filter $f(i,j)$ with the length (P) and width (Q) respectively. In each time sequence produces its own feature map. In contrast, this component influences the number of characteristics in convolutional networks. The number of characteristics in each layer of a standard MHCNN is computed using equation (4).

$$G = f_n * f_s * l + bia \quad (4)$$

Where f_s denotes to the size of the filter, f_n denotes the number of filters, and l denotes the last dimension of the resultant vectors.

The convolutional component of this architecture aims to extract as many attributes as possible from sensor input. The act of applying a filter and sliding it across process data is analogous to convolution. The total number of Windows is computed as follows:

$$W_n = \frac{D_n - W_l}{W_s} \quad (5)$$

where W_l indicates the length of the window, W_s refers to the window steps, and D_n denotes the total number of data points in the time series, which is seized to move the window over the time series. Multi-channel CNN is used in various time sequences, with each channel representing a distinct type of variable. The Multi-head CNN processes numerous time series by applying multiple one-dimensional convolutions to a single channel.

$$MH = concat(h_1, h_2, \ldots \ldots h_n) * T \quad (6)$$

The multi-head (MH) fuses the h_1, h_2, … hn with the transformation matrix (T). When dealing with several time series. The SoftMax function, which evaluates the probability of each class and then picks the highest number, yields a more accurate result. The fundamental mathematical SoftMax activation function is:

$$softmax(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{k} e^{x_i}} \quad (7)$$

In the SoftMax function, x represents the input. As a consequence, the output function will total to one in order to provide a proper probability distribution. As a result, the proposed approach, which employs the cross-entropy loss function, has the potential to capture important information at both the local and global levels. The loss function for cross-entropy is approximated as:

$$loss = -\frac{1}{N}\sum_{n=1}^{N}[y_n \log \widehat{y_n} + (1-y_n)\log(1-\widehat{y_n})] \quad (8)$$

If N is the number of samples, then yn is the probability of the actual label and yn is the probability of the predicted label. This probability distribution is reliant on the input fault type; hence it has been normalized to better classification results.

4. RESULT AND DISCUSSION

The proposed S-Belt wearable for monitoring of elder people monitoring. The alterations are in charge of controlling emotions and observing social cues. Figure 3 is a sample SMS alert message delivered to the carer when a person is discovered to be under a lot of stress.

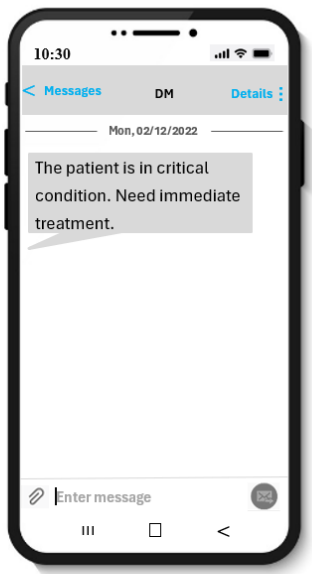

Figure 3. SMS notification

The proposed system was tested on one elder patient with two recordings for each elder, as shown in Table 1. The initial recording establishes a baseline measurement of the elder's resting heart rate (70 bpm) based on the elder's age. The autonomic nerve system, which regulates emotions, influences heart rate, which varies depending on the elder's mood.

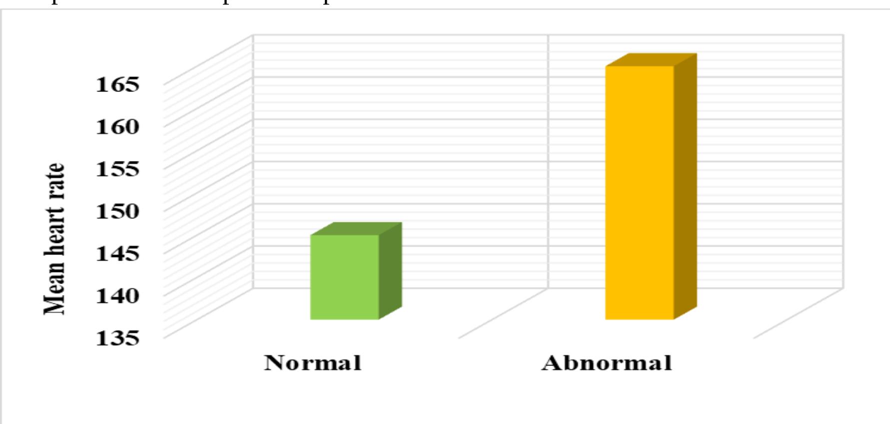

Figure 4. Detection of normal and abnormal heart rate

Figure 4 illustrates how the proposed system detect the heart rate (normal or abnormal) of one elder people in the testing dataset to alter in response to changes in heart rate. Researchers looked into the relationship between certain heart rate patterns. It also revealed aberrant heart rate responses to stressors and compared the levels of homocysteine and other biomarkers in elder to those in age-matched healthy elder people. It is clear that a elder's heart rate rises to between 60–100 beats per minute (bpm) when it falls to between 70 and 130 bpm when they are abnormal. Therefore, especially in elder patient, the pulse can be a powerful signal for identifying emotions. The suggested approach also enables family to interact with their elders effectively.

4.1. Performance analysis

Based on the precise parameters of ACU, PRE, REC, and F1S, the proposed method proficiency was assessed.

$$Accuracy\ (ACU) = \frac{P_T + N_T}{Total no. of samples} \tag{9}$$

$$Precision\ (PRE) = \frac{P_T}{P_T + P_F} \tag{10}$$

$$Recall\ (REC) = \frac{P_T}{P_T + N_F} \tag{11}$$

$$F1\ score\ (F1S) = 2\left(\frac{Precision * Recall}{Precision + Recall}\right) \tag{12}$$

Where P_T and N_T refer to the child's emotional state's real positives and negatives, respectively, P_F and N_F refer to the state's false positives and negatives. Table 2 provides evidence of the planned proposed method suitability for classifying diverse condition states.

Table 2. Performance assessment of the S-Belt method

Classes	ACU	PRE	REC	F1S
Normal	99.45	97.02	96.17	97.23
Abnormal	99.83	96.05	97.02	96.65

Table 2 shows the effectiveness gained by the proposed method for classifying two classes such as normal, and abnormal. ACU, PRE, REC, and F1S are used to evaluate competency. The proposed method achieves a 99.46% accuracy rate. Additionally, the S-Belt achieves scores of 99.64%, 96.53%, 96.59%, and 96.94% for overall accuracy, precision, recall, and f1.

4.2. Comparative analysis

The proposed method was contrasted with a variety of other methods in order to show how effective it is. In a comparison study, the S-Belt is compared to three other techniques. Table 3 compares the overall performance of deep learning models to the proposed strategy. Comparison of MHCNN against other DL models such as DNN, RNN, and CNN. Performance evaluation was based on various metrics such as ACU, PRE, REC, and F1S of the DL technique. The proposed methodology produces the maximum accuracy when compared to the existing approaches.

Table 3. Comparison between four deep learning networks

Networks	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
DNN	90.06	88.98	91.49	93.87
RNN	95.22	87.59	90.23	92.42
CNN	98.76	92.87	94.37	93.90
MHCNN (ours)	99.64	96.53	96.59	96.94

The proposed model is contrasted against three current methods in a comparative analysis. The overall efficacy of DL models and the suggested strategy are compared in Table 3. DL techniques like DNN, RNN, and CNN are contrasted with the MHCNN. Compared to DNN, RNN, and CNN, the accuracy range is improved by MHCNN network by 9.5%, 4.42%, and 0.8%, respectively.

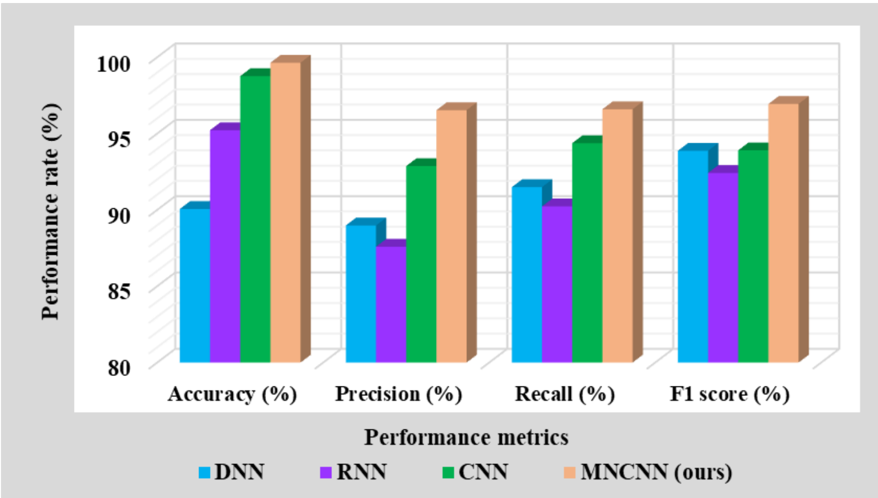

Figure 5. Comparison analysis of existing deep learning models

Traditional networks like DNN, RNN, and CNN gain less accuracy in compared to MHCNN. MHCNN achieves 99.64% accuracy, which is very high. From Figure 5 shows that the accuracy obtained by DNN, RNN, and CNN is 90.06%, 95.22%, and, 98.76%. The precision is obtained by DNN, RNN, and CNN and MHCNN is 88.98%, 87.59%, 92.87%, and 96.53%. The recall is obtained by DNN, RNN, and CNN and MHCNN is 91.49%, 90.23%, 94.37%, and 96.59%. The F1S is obtained by DNN, RNN, and CNN and MHCNN is 93.87%, 92.42%, 93.90%, and 96.94% respectively. The accuracy rate of the MHCNN is higher than that of the models currently in use.

Table 4. Accuracy comparison of proposed vs existing models

Author	Method	Accuracy (%)
Ali, F., [12]	Smart healthcare system	98.5
Rajan Jeyaraj, P. [14]	DNN-based accurate Signal Prediction	97.2
Proposed	S-Belt	99.64

The performance criteria in Table 4 were used to compare current approaches based on their accuracy. However, conventional networks fared less better than the new technique. The S-Belt improves the overall ACU range by 1.14%, and 2.44%, and 0.64% compared to Smart healthcare system [12], and DNN-based accurate signal prediction [14] respectively.

5. CONCLUSION

In this research, a S-Belt for monitoring of elder people using IoT is a smartphone application that predicts a health monitor for elder people and then sends that status together with the health state and anticipated behaviour to the family. Initially, the sensors in the smart belt such as temperature sensor, heartbeat sensor, oxygen sensor, and glucometer are used to gather data from the elders. The details from the sensors will be preprocessed using SWT technique and then classified using MHCNN. Then the classified result will be sent to the end users such as doctors and their relatives through a mobile application. The simulation finding shows proposed method performance was evaluated in terms of ACU, PRE, REC, and F1S. The S-Belt achieves the overall ACU of 99.64%. MHCNN network improves the accuracy range by 9.5%, 4.42%, and 0.8% better than DNN, RNN, and CNN. The S-Belt increases the overall ACU range by 1.14%, and 2.44%, and 0.64% compared to Smart healthcare system [12], and DNN-based accurate signal prediction [14] respectively.

CONFLICT OF INTEREST

The authors declare that they have no conflict ofinterest.

FUNDING

This research received no specific grant from anyfunding agency in the public, commercial, or notforprofit sectors.

ACKNOWLEDGMENT

The Author with a deep sense of gratitude wouldthank the supervisor for his guidance and constant support rendered during this research.

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Arrived: 05.12.2023
Accepted: 14.02.2024