E3S Web of Conferences **552**, 01095 (2024) https://doi.org/10.1051/e3sconf/202455201095
ICMPC 2024

Enhancing sleep pattern assessment with bio-compatible smart materials

Dhaval Makwana[1*], *Zahraa* Najah[2], *Devendra* Soni[3], *Hima* Bindu Valiveti[4], *Rakesh* Chandrashekar[5], *Ginni* Nijhawan[6], *P* Yakaiah[7]

[1]Research scholar, Mechanical and Aerospace Engineering department, Institute of Infrastructure Technology Research and Management (IITRAM), Ahmedabad.
[2]Hilla University College, Babylon, Iraq.
[3]Department of Civil Engineering, IES Institute of Technology and Management, IES University, Bhopal, Madhya Pradesh, India.
[4]Department of ECE, GRIET, Bachupally, Hyderabad, Telangana, India.
[5]Department of Mechanical Engineering, New Horizon College of Engineering, Bangalore, India.
[6]Lovely Professional University, Phagwara, India.
[7]Department of Electronics and Communication Engineering, MLR Institute of Technology, Hyderabad, Telangana, India-500049

Abstract. Biomaterials with intelligence can respond to variations in physiological factors. Additionally, they react to external stimuli that influence many attributes of allopathic drugs (technological advances medicine). Smart biomaterials are employed in a variety of therapies to enhance the care of different illnesses. Bio-based smart materials can be molded into a variety of soft designs, such as textiles, hydrogel, membranes film, aerogels, nanofibers, and fabrics, which are advantageous for wearable sensors when compared to polymers generated from petroleum. In this paper, sleep patterns are examined closely in relation to mental health, with a particular focus on bio-signal processing in identifying sleep-related disorders. According to the study, sleep stage analysis is critical to improving therapeutic outcomes for individuals suffering from depression due to its physiological influence. Biologically compatible smart devices enhance advanced biological capture techniques such as electroencephalography (EEG), electrocardiogram (ECG), and electromyography (EMG). As a result, these features increase sensor reliability, accuracy and reliability, ensuring high signal fidelity. The use of biocompatible smart-material based devices with artificial intelligence provides a revolutionary approach to the diagnosis of complex interconnected disorders of mental illness, sleep disorders and schizophrenia, including neural changes and its recurrence to identify sleep phases and identify trauma-related disturbances, and sophisticated machine learning provides in-depth insights.

Keyword. Bio-based-smart materials, sleep disorders, mental health, bio-signal recording

* Corresponding Author: dhaval.makwana.17pm@iitram.ac.in

1 Introduction

Issues with sleep are essential diagnostic criteria for mental ailments, specifically despair sufferers, as they raise the threat of suicide, relapse, or different negative effects that call for further medicine. Antidepressants affect the structure of sleep; some lead to development, at the same time as others cause deterioration. It is essential to recognise these influences with the intention to treat depression successfully. The development of micro biosensing technology with smart materials, going over how it's used in wearable and implantable devices as well as in vivo and in vitro systems, including energy supply and signal transmission. The sleep physiology, common sleep disruptions in depression patients, and the impact of several antidepressants, including new medications, on sleep in clinical practice are all covered in [1]. Recent research has shown that depression and sleep disruptions are related. This information may help physicians choose the best course of treatment for depressed patients who also have sleep abnormalities. Sleep problems are common, reported by a quarter of parents with children under the age of 5 years, and have been associated with poor behavior, worse school performance, and obesity, in addition to negative secondary effects on maternal and family well-being [2]. Due to insufficient training and ignorance of sleeping physiology, which is governed by chronological and homeostasis processes, pediatricians frequently underdiagnose problems with sleep. The non-REM and REM sleep phases, which include dynamic neurophysiologic methods, are part of the structure of sleep. Over the first 5 years, these systems alter, altering sleep and arousal.

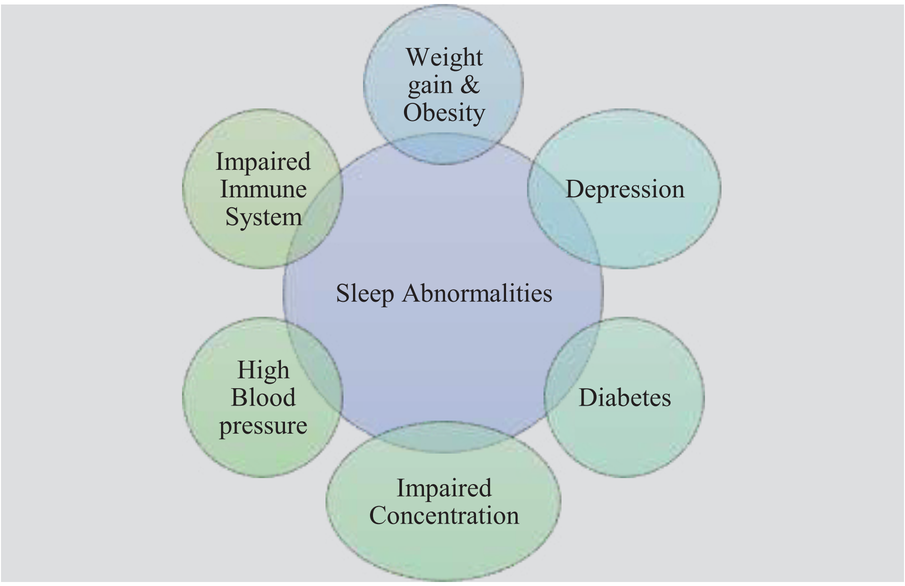

Fig. 1: Causes of Sleep disorders

Pediatricians need to be aware of the duration and patterns of children's sleep as it is essential to their daily functioning and behavior. In addition to contextual impacts including cultural and regional considerations, effective therapy takes into account the child's and parent's aspects. The American Academy of Pediatrics advises parents to encourage healthy sleep habits for their children beginning in infancy and continuing throughout childhood. This requires knowledge of physiology, development patterns, sleep regulation, the ideal amount of time for sleep, and other relevant topics. The concept of learning while anyone sleep, popularized by science fiction films and gadgets that promise to teach languages, facts, and help people stop smoking, has fueled advances in psychology [3]. It has been demonstrated previously that the sleeping brain is incapable of learning complicated information, but newer therapies indicate that sleep may be controlled to reinforce recent memories. Depression and sleep disturbance are intimately related as shown in Fig. 1. Adolescence is associated with a rise in insomnia and serious depression, which mostly affects women and causes a range of subjective sleep problems. The results of polysomnographic research on teenagers with depression are mixed, showing characteristics that are somewhat comparable to those of adults with depressive illness.

The variability in depression among adolescent's spectrum and disease the stage, together with maturational factors, might be the cause of the inconsistent results. Uncertainty exists regarding the precise neurobiological processes relating sleep disorders and depression. Adolescent depression can cause circadian rhythms altered beyond what is considered healthy, which might interfere with sleep. There are methods used to lessen depression, but there isn't enough evidence to support them. Reducing sadness and raising quality of rest might be the results of this understanding [4]. Convolutional in nature and recurrent neural networks are utilized in a novel model for prediction to predict sleep phases from radio data in the absence of sensors, identifying properties unique to each stage of sleep and capturing temporal progression. Our method significantly outperforms previous methods by using a modified adversarial training regime and removing unnecessary information for prediction tasks. Sleep architecture variations in chronic traumatic brain injury (TBI) and its association to TBI severity were investigated in a comprehensive review and meta-analysis, which also revealed possible changes in sleep quality. Consistent with [5], a small concussion has no effect on sleep architecture, while continuous TBI produces decreased sleep efficiency, reduced stage 2, and more advantageous slow wave sleep. The work presents credence to the principle that brain reconfiguration and reorganization with mild-to-extreme TBI cause greater sleep disruptions (SWS), therefore directing future research toward extra truthful biomarkers.

2 Sleep Physiology through Bio-signal Processing

By using efficiently diagnosing and treating sleep troubles related to respiratory and motion, this research improves medical reviews and treatments by the usage of electrocardiography and electromayography. Bio-signal processing extracts traits related to coronary heart rate and respiratory from the ECG the use of statistical moments, entropy, and EMG functions. A neural network structure and an iterative pulse top identification technique are advanced for this motive [6]. With a mean F1 rating of 0.57 and an average accuracy of 72%, the deep learning system efficaciously diagnoses patients with OSA, RLS, and both problems. the use of a spread of bio-signal recordings, such as respiratory, pulse oximetry, electroencephalography, electrocardiography, electromyography, and electrooculography, sleep staging is an important step inside the evaluation of polysomnographic information. The evaluation in [7] addresses the need for sophisticated but honest sleep staging evaluations to improve the interpretation of polysomnographic facts. It focuses on automated sleep staging strategies employing bio-signal recording and tackles each present and future problems. In this study, a 3-d-CNN version for classifying sleep levels is put forward, which uses time, frequency, and move-frequency characteristics from EEG, EMG, and EOG channel. Whereas 2D convolutional layering and partial dot-product attention layers identify significant channels and frequencies in various sleep stages, the model employs 3D convolution layers to learn intrinsic relationships among bio-signals and frequency bands [8]. In order to develop transit rules, a lengthy short-term memory unit is introduced. This results in competitive classification performance on the ISRUC-S3 and ISRUC-S1 sleep-disorder datasets, outperforming state-of-the-art baselines. In unwell participants, the ISRUC-S1 algorithm showed great accuracy, F1-score, and Cohen's kappa; on the ISRUC-S3 subset, its training time was 4493s, indicating its maximum computation speed.

Physiological signals including heart rate, sleep quality, early illness diagnosis, and human emotional state recognition are used in medical techniques such as ECG, EDA, EMG, and ICG. To help with machine learning and recognition of patterns, this work proposes a biosignal-specific method for analyzing and extracting features from physiological signals. In order to facilitate classification tasks such as model training and computation, this work proposes techniques for signal-specific filtering, segmentation, and extraction of features in an open-source program called MATLAB that is compatible to the MathWorks Classifier Learners app [9].

Deep learning techniques use bio-signals to enhance sleep stage categorization; nevertheless, individual bio-signal variations lead to inconsistent model performance on each new person. The study in [10] suggests a novel method called MetaSleepLearner, a transfer learning framework, to help physicians and lessen burden by teaching fresh patients how to stage slumber utilizing data from an extensive data set. In comparison with conventional gets closer, the Meta Sleep Learner strategy showed a statistically significant change in mean performance, demonstrating fair learning results and a considerable improvement in learning. By fine-tuning recordings of healthy individuals and people, Meta Sleep Learner, an innovative pre-training approach, outperforms traditional sleep phases identification techniques and reduces the workload of physicians. The study in [11] examines the state-of-the-art in deep learning with physical signals data, such as EMG, ECG, EEG, and EOG. It does this by reviewing 147 publications that were released between January 2018 and October 2019. The goal of the study is to apply this strategy to medical activities. Examining and contrasting deep learning methods for physiological signal analysis in medical applications, this research concentrates on training architecture, model, task, dataset reports, and input data type. Based on data modality, medical application, training architecture, and dataset sources, research on deep neural network techniques for physiologic signal evaluation has grouped.

3 Types of Bio-signals Used in Sleep Analysis

Using a variety of bio-signal recordings, such as respiratory, pulse oximetry, electroencephalography, electrocardiography, electromyography, and electrooculography, sleep staging is an essential step in the analysis of polysomnographic data. The review in [12] addresses the need for sophisticated, effective sleep staging evaluation techniques that use bio signal recording to improve the comprehension of poly so mono graphic data while addressing present and future issues. Common physiological reactions like sleepiness are associated with poor energy, impaired cognitive function, and inadequate sleep. There are a few investigations involve physiologic prediction and mainly on operating while drunk. Utilizing brainwave, eye tracker, heart rate, and galvanic skin response sensors to capture physiologic alterations in people, the study employed five tests to investigate the chance of mishaps caused by sleepiness. Brain wave activity, eye movement, heart rate, and GSR were monitored during drowsiness and tiredness in [13]. Changes were analyzed, and a classification model was used to predict the participant's status. Artificial neural networks, support vector machines, back propagation systems, and SDK coding were used to handle brain wave and GSR information. 90% of those who participated were happy with SVM's optimum classification efficiency, which yielded a precision of 89.1%. Artificial Intelligence (AI) is improving decision-making, patient status monitoring, diagnosis, and staff communication. In healthcare, AI algorithms can monitor the condition the tissues, forecast health issues, and guard from possible threats to health. This study in [14] investigates the use of AI to medical diagnostics, emphasizing case studies, bio-signals, and novel difficulties in health state prediction.

Table 1: Bio-Signal Utilization in Sleep and Drowsiness Detection

Study Focus	Smart material based Bio-signals processing	Methodology	Key Findings	Accuracy	Potential Clinical Applications
Sleep Staging Evaluation	EEG, ECG, EMG, EOG, Respiratory	SVM, ANN, Backpropagation, SDK coding	High classification efficiency with SVM; improved understanding of polysomnographic data	89.1%	Polysomnography, sleep disorder diagnosis
Physiologic Prediction for Drowsiness	Brainwave, Eye Tracker, Heart Rate, GSR	Artificial neural networks, support vector machines	Prediction of accidents caused by sleepiness; monitoring of drowsiness and tiredness	90%	Driving safety, workplace alertness monitoring
Wearable Technology in Health Monitoring	General biometric signals	Comparative analysis, Wearable device design	Potential for clinical use in bio-signal and disease monitoring; challenges in design and analysis	-	Personal health monitoring, lifestyle decisions
EMD for EEG Sleep Disorder Diagnosis	EEG	Empirical Mode Decomposition (EMD), MC-SVM classification	Effective in diagnosing sleep disorders; identification of optimal IMF levels	93.24%	Early detection and care for sleep-related issues
Automated Sleep Phase Diagnosis	ECG	Heart Rhythm Variability, Decision-Tree-Based SVM	Non-invasive method promising for home diagnostic devices; saves time and resources	89.2%	Home-based sleep monitoring, sleep stage detection

Technological developments in data gathering, sensor design, and smart device connectivity have resulted in an explosion of personal health-tech products, allowing for the tele monitoring of body dynamics and encouraging lifestyle decisions. In spite of their user-friendly interface for monitoring bodily variables, wearable technology has clinical uses for bio signal and illness monitoring, which are the subject of this [15]. In order to establish criteria for creating wearable technology that is clinically useful, this review research examines potential and challenges in bio signal analysis, wearable device design, and comparing wearable bio signals with clinical counterparts.

Sleep disturbances have an influence on illnesses such as mental depression. Early detection can enhance care and perhaps save lives. Brain activity is recorded by the EEG signal, and EMD is a useful method for processing and interpreting EEG data. The study in [16] uses the technique of empirical mode decomposition (EMD) for EEG signal analysis and proposes a methodology for choosing the best intrinsic mode functions (IMFs) for EMD in order to diagnose issues with sleep using EEG brain signals. In order to identify sleep-related problems, the EMD segmentation methodology separates IMF ranges using the MC-support vector machinne based categorization algorithm. To find the best EMD IMF for detecting sleep problems, performance is categorized for a number of IMFs. An experiment utilizing a standard dataset indicates the proposed method outperforms the current IMF 8 model, with a median accurate classification of 93.24%. In contrast to conventional poly so mono graphic to (PSG), the study in [17] suggests a technique for automated sleep phase diagnosis using electrocardiograms (ECGs). This approach may be used to enable non-invasive, home-diagnostic devices while also saving time and money. The Heart Rhythm Variability spectrum evaluation from ECG is used by an autonomous sleep stage identification method, which is categorized using Decision-Tree-Based Support Vector Machines. The algorithm's accuracy of 89.2% shows its promise for further study in sleep stage detection

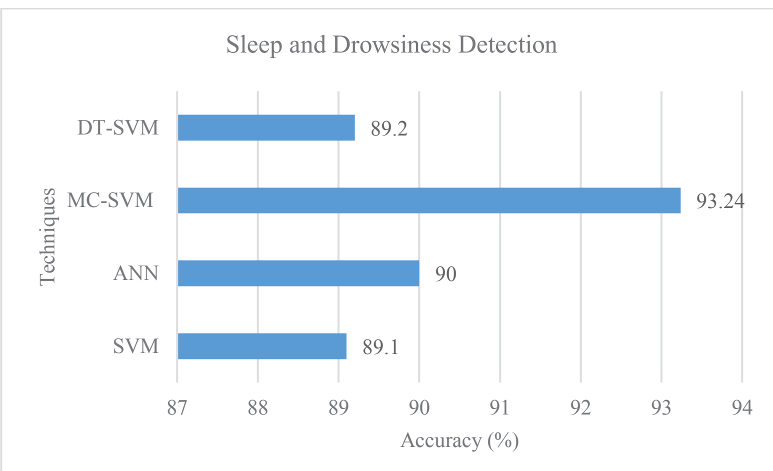

Fig. 2: Sleep and Drowsiness Detection

The graph in Fig. 2, summarizes the accuracies of numerous machine learning strategies used for bio-signal evaluation in sleep and drowsiness detection. SVM achieves an accuracy of 89.1%, ANN slightly higher at 90%, while MC-SVM shows the excellent performance with 93.24% accuracy. DT-SVM also performs comparably, with an accuracy of 89.2%. those effects show the effectiveness and variant of these computational methods in decoding bio-indicators for scientific diagnostic purposes.

4 Noise Reduction and Artifact Removal in Bio-signal Data

Accurate analysis of bio signals can be challenging due to their low S/N ratio and frequent contamination from both internal and external issues. This may lead to inaccurate disease diagnosis or deceptive feedback in biosignaling-based systems. Biosignal recordings have been subjected to artifact removal and identification using signal processing-based methods, which have been used to popular BCIs and neural prosthesis. The study in [18] addresses noises and artifacts in biosignal recordings, explains how they vary from signals of interest, and explores sophisticated signal processing methods for accurate identification and distortion-free removal. With an emphasis on artifact and noise reduction for BCI and medical diagnostic uses, the study in [19] examines biosignal recordings in the time, frequency, and tensor domains. It evaluates the computational complexity and cost of algorithms and shows how the efficacy of algorithms may be enhanced by a priori clinical or statistical knowledge. Advancements in wireless communication and MEMS sensor technology have led to increased body area communication in healthcare. However, motion artifacts can lead to incorrect predictions, necessitating denoising bio signals for accurate diagnosis and analysis. Using a neurokit dataset, the study in [20] demonstrates that L1 outperforms L2 in signal quality as determined by SNR and proposes a regularized denoising autoencoder (DAE) for reconstructing clean signals from noisy ones.

Table 2: Bio-signal Processing Techniques in Healthcare

Focus Area	Signal Domain Analyzed	Key Techniques and Tools	Key Findings	Signal Quality Metrics	Applicable Fields
Artifact Removal in Biosignal Recordings	Time, Frequency, Tensor	Sophisticated signal processing methods	Identifying and removing distortions effectively	Computational Complexity, Algorithm Cost	BCI, Medical Diagnostics
Motion Artifact Reduction	-	L1 Regularization, Denoising Autoencoder (DAE)	L1 outperforms L2 in signal quality	SNR	Wireless Healthcare Communications
Noise Reduction Techniques in Healthcare	-	Mathematical models, Signal processing advancements	Need for robust methods in wearable healthcare tech	-	Wearable Device Implementation
ECG Denoising and Morphological Analysis	Time and Frequency	Wavelet-VBE, EMD-MAF, GAN2, GSSSA, MP-EKF, DLSR, AKF	Effective removal of various ECG noises and artifacts	-	ECG Analysis, Cardiac Evaluation
ECG Signal Enhancement	Time and Frequency	Digital filters, Discrete wavelet transform (DWT)	DWT with db8 mother wavelet provides best SNR and lowest RMSE	SNR, RMSE	ECG Analysis, Clinical Diagnostics
ECG Noise and Artifact Reduction	-	Combined high pass and low pass filtering method	Early detection of heart-related disorders	-	ECG Technology, Clinical Applications

Signal quality is essential for bio-signal processing performance, and one important duty is noise reduction. Robust approaches are needed for wearable device implementation in healthcare technology. Sensor technology advancements provide trustworthy data collecting for medicinal applications. The study in [21] analyzes the methods of noise reduction applied in earlier publications, emphasizing the requirement for mathematical models to appropriately capture the nature of signals and the developments in the field of signal processing. This study in [22] examines the design concepts and workflow of many techniques for identifying morphological abnormalities in an electrocardiogram (ECG), grouping them into distinct groups for comparative analysis and the creation of contemporary techniques for denoising ECG. Wavelet-VBE, EMD-MAF, GAN2, GSSSA, MP-EKF, DLSR, and AKF are shown to be the best appropriate for additive white Gaussian noise removal when the study evaluates several ECG denoising algorithms on MIT-BIH datasets, PTB, QT, and other databases Muscle artefacts, base-line wander, electrode motion artefacts, power-line interference, FCN-based DAE, DWT, MABWT, CPSD sparsity, and UWT may all be effectively removed with GAN1, MP-EKF, DLSR, AKF, and GAN1. With its clear signal that greatly affects the structural and functional performance of the heart, the electrocardiogram (ECG) is an essential tool for cardiac evaluation, problem identification, and clinical diagnosis. Using digital filter designs and discrete wavelet transform with mother wavelets, this study examines several approaches for improving and reducing ECG noise. To ensure accurate and trustworthy ECG analysis, it looks into and compares their performance in terms of Signal-to-Noise Ratio (SNR) and Root Mean Square Error (RMSE) [23]. Discrete wavelet transform using db8 as mother wavelet achieves the greatest SNR value and lowest RMSE value when it comes to de-noising and upgrading raw ECG data, surpassing both Finite Impulse Response and Infinite Impulse Response digital filtering designs. Much less distortion can be performed whilst evaluating ECG facts within the time and frequency domain names with the discrete wavelet transform technique. because coronary heart-associated problems are so commonplace and costly for society, early identity is critical. The broadly to be had, low-cost, and radiation-free ECG technology needs noise and artefact reduction. A filtering technique that combines a high pass and a filter out with a low bypass is presented in [24].

5 Conclusion

This study provides the critical role of bio-based smart materials in signal processing in detection of sleep styles, particularly within the context of mental health evaluation and treatment. by using exploring numerous bio-signals and their packages in sleep analysis, alongside superior noise discount techniques, the study highlights the capacity for improved diagnostic accuracy and treatment efficacy. furthermore, the combination of machine learning algorithms gives promising avenues for automating sleep phase analysis and physiological prediction, paving the manner for future advancements in medical sleep monitoring.

- Bio-signal Processing Advances: utilizing various bio-signals which includes smart material-based EEG and ECG sensors, coupled with advanced signal processing strategies, holds promise for reinforcing sleep evaluation and diagnostic precision.
- Machine learning applications: machine learning algorithms, consisting of SVM and ANN, show effectiveness in automating sleep segment analysis and physiological prediction, imparting insights into the future of clinical sleep monitoring.
- Mental fitness Implications: Sleep disturbances are closely related to mental fitness disorders like melancholy, emphasizing the importance of correct sleep analysis in diagnostic medication.

References

1. Hutka, Peter, Michaela Krivosova, Zuzana Muchova, Ingrid Tonhajzerova, Andrea Hamrakova, Zuzana Mlyncekova, Juraj Mokry, and Igor Ondrejka. "Association of sleep architecture and physiology with depressive disorder and antidepressants treatment." International journal of molecular sciences 22, 3 (2021): 1333.
2. Bathory, Eleanor, and Suzy Tomopoulos. "Sleep regulation, physiology and development, sleep duration and patterns, and sleep hygiene in infants, toddlers, and preschool-age children." Current problems in pediatric and adolescent health care 47, 2 (2017): 29-42.
3. Cellini, Nicola, and Sara C. Mednick. "Stimulating the sleeping brain: Current approaches to modulating memory-related sleep physiology." Journal of neuroscience methods 316 (2019): 125-136.
4. Urrila, A. S., T. Paunio, E. Palomäki, and M. Marttunen. "Sleep in adolescent depression: physiological perspectives." Acta Physiologica 213,4 (2015): 758-777.
5. Zhao, Mingmin, Shichao Yue, Dina Katabi, Tommi S. Jaakkola, and Matt T. Bianchi. "Learning sleep stages from radio signals: A conditional adversarial architecture." In International Conference on Machine Learning, 4100-4109. PMLR, 2017.
6. Mantua, Janna, Antigone Grillakis, Sanaa H. Mahfouz, Maura R. Taylor, Allison J. Brager, Angela M. Yarnell, Thomas J. Balkin, Vincent F. Capaldi, and Guido Simonelli. "A systematic review and meta-analysis of sleep architecture and chronic traumatic brain injury." Sleep medicine reviews 41 (2018): 61-77.
7. Girish, K. M., Naik, R., Prashantha, S. C., Nagabhushana, H., Nagaswarupa, H. P., Raju, K. A., ... & Nagabhushana, B. M. (2015). Zn2TiO4: Eu3+ nanophosphor: self explosive route and its near UV excited photoluminescence properties for WLEDs. Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 138, 857-865.
8. Damodharan, D., Rajesh Kumar, B., Gopal, K., De Poures, M. V., & Sethuramasamyraja, B. (2019). Utilization of waste plastic oil in diesel engines: a review. Reviews in Environmental Science and Bio/Technology, 18(4), 681-697.
9. Girish, K. M., Prashantha, S. C., Nagabhushana, H., Ravikumar, C. R., Nagaswarupa, H. P., Naik, R., ... & Umesh, B. (2018). Multi-functional Zn2TiO4: Sm3+ nanopowders: excellent performance as an electrochemical sensor and an UV photocatalyst. Journal of Science: Advanced Materials and Devices, 3(2), 151-160.
10. Naik, R., Prashantha, S. C., Nagabhushana, H., Sharma, S. C., Nagaswarupa, H. P., Anantharaju, K. S., ... & Girish, K. M. (2016). Tunable white light emissive Mg2SiO4: Dy3+ nanophosphor: its photoluminescence, Judd–Ofelt and photocatalytic studies. Dyes and Pigments, 127, 25-36.
11. Rathod, V. P., & Tanveer, S. (2009). Pulsatile flow of couple stress fluid through a porous medium with periodic body acceleration and magnetic field. Bulletin of the Malaysian Mathematical Sciences Society, 32(2).
12. Rim, Beanbonyka, Nak-Jun Sung, Sedong Min, and Min Hong. "Deep learning in physiological signal data: A survey." Sensors 20, 4 (2020): 969.
13. Chriskos, Panteleimon, Christos A. Frantzidis, Christiane M. Nday, Polyxeni T. Gkivogkli, Panagiotis D. Bamidis, and Chrysoula Kourtidou-Papadeli. "A review on current trends in automatic sleep staging through bio-signal recordings and future challenges." Sleep medicine reviews 55 (2021): 101377.
14. Horng, Gwo-Jiun, and Jia-Yi Lin. "Using multimodal bio-signals for prediction of physiological cognitive state under free-living conditions." IEEE Sensors Journal 20, 8 (2019): 4469-4484.
15. Swapna, Mudrakola, Uma Maheswari Viswanadhula, Rajanikanth Aluvalu, Vijayakumar Vardharajan, and Ketan Kotecha. "Bio-signals in medical applications and

challenges using artificial intelligence." Journal of Sensor and Actuator Networks 11, 1 (2022): 17.
16. Athavale, Yashodhan, and Sridhar Krishnan. "Biosignal monitoring using wearables: Observations and opportunities." Biomedical Signal Processing and Control 38 (2017): 22-33.
17. Indira, D. N. V. S. L. S., Ganiya, R. K., Babu, P. A., Xavier, A. J., Kavisankar, L., Hemalatha, S., ... & Yeshitla, A. (2022). Improved artificial neural network with state order dataset estimation for brain cancer cell diagnosis. BioMed Research International, 2022.
18. Jaidass, N., Moorthi, C. K., Babu, A. M., & Babu, M. R. (2018). Luminescence properties of Dy3+ doped lithium zinc borosilicate glasses for photonic applications. Heliyon, 4(3).
19. Lakshmi, L., Reddy, M. P., Santhaiah, C., & Reddy, U. J. (2021). Smart phishing detection in web pages using supervised deep learning classification and optimization technique ADAM. Wireless Personal Communications, 118(4), 3549-3564.
20. Spandana, K., & Rao, V. S. (2018). Internet of Things (Iot) Based smart water quality monitoring system. International Journal of Engineering and Technology (UAE), 7(3), 259-262.
21. Kumar, K. U., Babu, P., Basavapoornima, C., Praveena, R., Rani, D. S., & Jayasankar, C. K. (2022). Spectroscopic properties of Nd3+-doped boro-bismuth glasses for laser applications. Physica B: Condensed Matter, 646, 414327.
22. Chatterjee, Shubhojeet, Rini Smita Thakur, Ram Narayan Yadav, Lalita Gupta, and Deepak Kumar Raghuvanshi. "Review of noise removal techniques in ECG signals." IET Signal Processing 14, no. 9 (2020): 569-590.
23. Chieng, Thion Ming, Yuan Wen Hau, Zaid Bin Omar, and Chiao Wen Lim. "Qualitative and quantitative performance comparison of ECG noise reduction and signal enhancement method based on various digital filter designs and discrete wavelet transform." International Journal of Computing and Digital Systems 9, 4 (2020): 553-565.
24. Kim, S., Baek, S., Sluyter, R., Konstantinov, K., Kim, J. H., Kim, S., & Kim, Y. H. (2023). Wearable and implantable bioelectronics as eco-friendly and patient-friendly integrated nanoarchitectonics for next-generation smart healthcare technology. EcoMat, 5(8), e12356.