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A ROBUST ARTIFICIAL NEURAL NETWORK APPROACH FOR EARLY DETECTION OF CARDIAC DISEASES

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Abstract
The research introduces a method focused on the early and precise prediction of cardiac conditions, enhancing treatment effectiveness. It leverages signal processing techniques for feature extraction. Utilized in this study are ten types of metal oxide semiconductor sensors to detect various gases released by the human body. Also, ECG, SPO2, and oxygen sensors contribute to data collection. The study conducts experiments involving groups of 5, 10, 15, and 20 participants, each providing 1000 unique features. These analog signals are converted to digital via Arduino. A specialized model architecture, trained on this newly created dataset, evaluates performance metrics such as sensitivity, f-measures, accuracy, and specificity. This model, designed to identify human odors, achieves an accuracy exceeding 85%.

INTRODUCTION

Chronic diseases, as documented by the World Health Organization (WHO), encompass a range of conditions, including cardiovascular diseases (CVD), chronic respiratory diseases, cancer, diabetes mellitus (DM), and neurodegenerative diseases [1]. These illnesses are recognized globally as fundamental and significant health challenges. Chronic diseases are the primary cause of mortality worldwide and contribute substantially to the global health burden [2]. Shared risk factors for these conditions include co-morbidities and socioeconomic aspects closely linked to each disease [3]. Diet plays a crucial role in the incidence of chronic diseases, typically characterized by high consumption of meats and fats and low intake of cereals and vegetables [4, 5]. Such dietary habits, coupled with sedentary lifestyles and increased tobacco and alcohol use, exacerbate these health issues [6].

Over the past decade, there has been a notable increase in the population of older adults living with chronic conditions, underscoring the necessity for essential healthcare services [7]. There is a pressing need to revolutionize healthcare to deliver efficient, innovative, and economical solutions that are accessible to patients anytime and anywhere in a user-friendly manner [8]. Society must adopt a preventive approach to disease management to delay the onset of treatment and facilitate effective interventions [9]. The utilization of self-tracking devices in healthcare has proven beneficial in promoting healthy behaviors among patients [10, 11]. These devices, which include wireless biosensors, can be used in various settings such as homes [12], vehicles, workplaces, and even implanted in the body [13]. Digital healthcare services and applications are increasingly available on mobile devices, including the integration of wireless medical sensor networks and radio frequency identification technology [14]. Self-monitoring empowers [15] individuals to actively manage their health daily. This review [16, 17] aims to assess current market offerings and requirements, highlighting opportunities for enhancing health outcomes. Such advancements [18] promise significant social and economic benefits, enabling individuals of all ages to lead independent, high-quality lives.

Cardiovascular disease remains the leading cause of mortality worldwide [19]. Notably, in 2019, approximately 616,000 deaths were attributed to heart-related conditions [20]. Advanced imaging technologies such as magnetic resonance imaging (MRI) [21-23], which utilizes radio waves and magnetic fields [24], play a crucial role in capturing dynamic images of the heart and major blood vessels. Additionally, echocardiography and computed tomography (CT) scans [25], employing X-ray imaging, provide detailed anatomical views of the heart [26].

The exploration of smart medical devices for monitoring cardiac health poses a significant research challenge within the medical and pattern recognition fields [27-29]. This study aims to develop methodologies that can proactively identify heart-related diseases before catastrophic health events occur [30, 31]. Specific biomarkers, including volatile organic compounds from human sweat, skin, breath, and emitted radiation, are under investigation for their potential in diagnosing cardiac diseases [32].

The primary goals of this research are to develop an automated system capable of analyzing a subject's cardiac health independently [33], detect and alert users to potential abnormalities, and create a more accurate and reliable cardiac disease monitoring system that operates without human intervention [14].

The research contributes significantly to the field of cardiac health monitoring by addressing crucial questions that could lead to ground breaking advancements in early diagnosis and preventive healthcare. Here are the main contributions highlighted by the study:

- Predictive Analysis from Heart Sounds: The study explores whether an acoustic analysis of heart sounds can predict imminent cardiac events, such as heart attacks. This involves sophisticated pattern recognition and signal processing technologies to detect subtle anomalies that precede major cardiac events.
- Identifying Signs and Symptoms in Heart Function: It also investigates whether there are specific signs and symptoms observable in the heart's function that can aid in the early diagnosis of cardiac-related diseases. This could include variations in rhythm, sound, or other cardiac parameters that are detectable before the disease progresses to a critical stage.

These contributions are pivotal as they could lead to the development of non-invasive, real-time monitoring tools that enhance preventive care and enable timely medical interventions, potentially saving lives by addressing cardiac issues before they escalate to emergencies.

This study is systematically organized into distinct sections to ensure a coherent presentation of the research. Section 1: Introduction provides an overview of the significance and objectives of the study, setting the context for the exploration of heart disease prediction. Section 2: The Literature Review delves into existing research, highlighting technological advancements and identifying gaps in the field of cardiac health monitoring. Section 3: Proposed Methodology outlines the sensors used, data collection processes, and analytical methods employed to predict cardiac diseases. Section 4: Result Analysis discusses the findings of the study, comparing them with previous works to evaluate the effectiveness of the proposed model. Section 5: Conclusion and Section 6: Future Work summarize the key outcomes, discuss their implications for clinical practice, and suggest potential areas for future research.

2. Literature Review

A recent study by [34] introduced a predictive system for heart disease utilizing a feature fusion approach combined with ensemble deep learning [35, 36]. Initially, the system merges electronic medical records and sensor data using a feature fusion method to generate healthcare data [37]. To enhance system performance and reduce computational load, a technique is employed that discards irrelevant features and retains crucial ones [12, 38]. Additionally, the performance is further optimized by employing conditional probability to calculate specific features for each class. An ensemble deep learning model is subsequently developed for the proactive detection of heart disease [39]. This model integrates feature weighting, fusion, and selection methods to analyze heart disease data effectively. Remarkably, this system achieves an accuracy of 98.5%, which is superior to previous models [40].

In another part of the study, a deep neural network (DNN) model was developed by [41], trained on a dataset of over 2 million labeled exams from the Telehealth Network of Minas Gerais, which was later examined in the CODE (Clinical Outcomes in Digital Electro-cardiology) study [42]. Traditional automatic electrocardiograms have been constrained by the accuracy limitations of prior models [43]. The DNN model, which learns through stacked examples, has shown exceptional success across various tasks, raising expectations for its potential to enhance clinical practices. Clinicians have identified six types of abnormalities in 12-lead ECG recordings, achieving a specificity of 99% and F1 scores above 80%. These results suggest that the integration of DNN technology with traditional ECG methods could standardize and improve clinical diagnostics [44].

A recent study [3] introduced a secure Internet of Health Things (IoHT) system designed to simplify the clinical diagnosis of cardiovascular diseases [45]. This system leverages deep learning algorithms and employs a tangle-based approach along with multi-factor authentication to ensure secure data processing. The IoHT framework is crafted to facilitate medical professionals by automating the classification of heart sounds using Autoencoders Neural Network (AEN). It utilizes two main datasets: the PASCAL B-Training and the PhysioBank-PhysioNet A-Training. For the PASCAL dataset, the AEN shows remarkable results with 100% sensitivity, 100% specificity, and 100% accuracy. In the PhysioNet dataset, it achieves 99.8% accuracy, 99.65% sensitivity, and 99.13% specificity. Comparative literature suggests that AEN-based solutions surpass other methods in accuracy [46]. Additionally, feedback from medical professionals based on the application of this system in 479 cases has been overwhelmingly positive. The system demonstrated an accuracy rate of 91.1% for detecting extra beats, 96.3% for normal heartbeats, and 90.11% for identifying blurred sounds. Security-wise, the system proves robust against synthetic data inputs and can be seamlessly integrated into mobile devices or central systems [47], enhancing its accessibility and utility in diverse clinical environments.

The study explores the development of health monitoring devices employing the Naive Bayes classifier [48, 49], specifically designed to detect the early stages of minor heart disease [50]. The system utilizes various diagnostic parameters such as fasting blood sugar [51], blood pressure, resting ECG, ST depression, maximum heart rate, the nature of chest pain, age, and the number of major vessels, gender, exercise-induced angina, and thalassemia. These parameters are critically assessed to determine the presence or absence of heart disease with high accuracy [52] .

Additionally, another segment of the research [53] focuses on a model that captures pulse rate data, plethysmogram data, and patient oxygen ratios [30]. This data, collected through IoT devices, is transmitted to a central database. The performance of this system is evaluated based on the accuracy of the data across various network topologies and the overall system flexibility [54]. This model was designed and tested at Ege University Hospital, employing a bespoke architecture tailored for biomedical applications and integrating a Wireless Body Area Network (WBAN) [20, 30].

The broader application of IoT in healthcare is highlighted as particularly effective in managing chronic diseases by facilitating early detection and timely medical intervention [55]. The article discusses potential future trends in medical technology, such as Nano-IoT and Bio-IoT, which could revolutionize patient monitoring and treatment [39].The most commonly utilized IoT system in healthcare is the WBAN, a compact device that can be embedded in or worn on the patient's body, providing continuous health monitoring [27, 56]. These advancements represent significant strides in leveraging technology to enhance healthcare outcomes.

Despite the significant advances in heart disease prediction models and monitoring systems, as reviewed from various recent studies, there still exists a critical research gap in the integration and real-time application of these systems in everyday clinical settings [31]. Most of the existing models [57], including deep learning and IoT-based systems [58], focus on accuracy and early detection but often overlook the practical deployment challenges such as real-time data processing, system interoperability, and user-centric design which are crucial for adoption in actual healthcare environments [57, 59, 60].

Also, while the accuracy of these models is commendable, the generalizability of such systems across diverse populations and varied clinical settings remains underexplored [61]. There is a notable gap in studies addressing the robustness of these systems against varied physiological and pathological conditions across different demographics. This gap highlights the need for more inclusive research that not only enhances the technical prowess of these models but also ensures their effectiveness and reliability in universal healthcare scenarios.

3. The proposed Methodology

The proposed methodology integrates a diverse array of sensors to capture volatile organic compounds and other biometric signals from patients, which are then processed using advanced machine learning algorithms to predict cardiac diseases shown in Figure 1. The data, once collected, undergoes preprocessing to enhance its quality before it is used to train a deep learning model. This comprehensive approach aims to enhance early detection and monitoring of heart conditions, ensuring high accuracy and reliability in real-world applications.

For the identification of odors, the process involves several key tasks that ensure accurate detection and analysis. These tasks are essential components of a comprehensive odor identification system, particularly in applications like environmental monitoring, quality control in manufacturing, or medical diagnostics. Here's a breakdown of each task:

- Odor Sensing: This is the initial step where specific sensors, typically electronic noses (e-noses) equipped with various sensor elements, detect the odor compounds. These sensors react to the chemicals present in the air, producing a pattern or signature that corresponds to the particular odor.
- Data Transmission: Once the odor has been detected and converted into a digital signal by the sensors, this data is transmitted to a processing unit. The transmission can be wired or wireless, depending on the system design, and is crucial for remote sensing applications.
- Data Receiving: At this stage, the transmitted data is received by the processing system. This system could be a dedicated computer, a cloud-based server, or a decentralized platform, where further analysis is prepared.
- Data Processing/Binning: The received data undergoes processing which might include noise reduction, signal amplification, and data normalization. Binning refers to the categorization of data into bins or clusters to simplify pattern recognition and analysis. This step is vital for reducing complexity and enhancing the accuracy of odor classification.
- Data Authentication: This final task ensures the integrity and security of the transmitted data. Authentication processes verify that the data received is indeed from a trusted and reliable source and has not been tampered with during transmission. This is especially important in applications where data security and accuracy are paramount, such as in medical diagnostics or environmental monitoring [62].

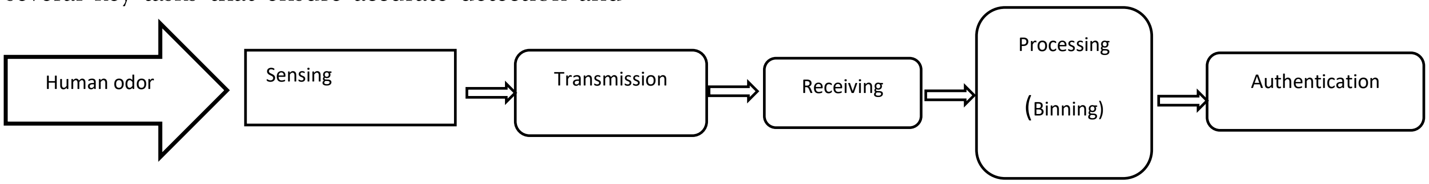

Figure 1: Structure of heart disease prediction at early stage

3.1 Dataset

The proposed model was evaluated using a substantial dataset, segmented into training and validation subsets. The training phase utilized three distinct datasets: the Hungarian, Telehealth Network of Minas Gerais (TNMG), and Cleveland datasets. Both the Hungarian and Cleveland datasets were sourced from the UCI (University of California, Irvine) Machine Learning Repository, a well-known resource for data mining and machine learning datasets. Specifically, the Hungarian dataset comprises 294 cases with 14 features, while the Cleveland dataset includes 303 cases with 76 features. Additionally, the S12L-ECGs dataset was employed, obtained from the Telehealth Network of Minas Gerais (TNMG). This dataset, which is publicly accessible, predominantly supports the Minas Gerais region in Brazil, encompassing 811 out of 853 datasets. Since 2017, TNMG has been providing tele-diagnosis services to regions including the Amazon and the northeastern zones of Brazil's states. This dataset is instrumental in predicting heart disease, although all datasets initially contained some missing values that were subsequently addressed using a specialized filtering approach designed for this study. The combined datasets enhance the robustness and comprehensiveness of the training phase. For validating the proposed method, the dataset from Bahawal Victoria Hospital (BVH) was utilized, ensuring that the model's effectiveness and applicability are rigorously assessed in a real-world clinical environment.

3.2 Preprocessing

Preprocessing is a crucial step that follows the acquisition of data, particularly when applying machine learning algorithms to the proposed method. Direct application of these algorithms on real-world data can be challenging due to its potential uncertainty, noise, and incompleteness. To facilitate the accurate prediction of heart disease, a preprocessing technique is applied to the dataset. This technique encompasses several processes, including feature selection, filtering, normalization, and feature weighting, each critical for preparing the data for effective analysis and ensuring reliable predictions.

3.3 Sensing

In the initial phase of the study, various sensors are employed to detect human odors, focusing primarily on the volatile organic compounds (VOCs) emitted through the skin. Human skin contains three types of glands, and the objective here is to identify VOCs that are consistently excreted and remain stable despite external factors. The production of odor involves bacterial activity on the skin [63], which interacts with glandular secretions [53].Setting a target for specific VOCs is crucial because humans emit a vast array of these compounds. However, the study targets primary VOCs that are significant contributors to body odor and are unaffected by age or environmental variables [54]. The investigation into human odor is complex due to the variety of glands and the different VOCs they emit. Notable groups of VOCs include aldehydes, ketones, alcohols, carboxylic acids, esters, hydrocarbons, and ethers. Select VOCs from these groups are specifically targeted in the study. To support this process, a range of sensors is utilized, including those for ECG, blood pressure, blood sugar, and cholesterol. Each sensor is selected for its unique ability to contribute to the broader task of detecting and analyzing the relevant VOCs effectively [64].

3.4 Transmission and receiving

After the data is captured by the sensors, it is transmitted using an Arduino UNO, a microcontroller board known for its simplicity and ease of programming. The Arduino functions by reading inputs, such as sensor data, and converting them into outputs. It operates based on programmed instructions that dictate which tasks to perform, such as data acquisition and signal conversion.

In this setup, the Arduino plays a crucial role in converting analog signals from various sensors into digital signals. These sensors detect different aspects of human body odor, and the Arduino ensures that these analog signals are accurately converted to digital form. The resulting digital data, which consists of the raw digital outputs representing human body odors, is then transferred to a computer system. Here, it undergoes further processing and authentication, enabling detailed analysis and application in subsequent stages of the research or application process. This method ensures that data handling remains structured and efficient, facilitating effective data utilization in odor detection and analysis projects.

3.5 Processing (Binning)

Data binning, also known as bucketing, is a crucial preprocessing technique that is employed when dealing with continuous data streams where the length of the digital data is undefined. This method is particularly essential in scenarios like odor detection, where sensors continuously gather vast amounts of data.

The primary purpose of data binning is to organize the continuous incoming data into manageable 'bins' or 'buckets' before it is stored. This process not only helps in structuring the data but also significantly reduces the complexity of subsequent data analysis by aggregating data into discrete intervals.

In the specific setup described, data is continuously collected and needs to be effectively managed to prevent overflow and ensure efficiency. Therefore, the system is configured to store the incoming digital data for a brief duration, such as 5 seconds, before it is binned and subsequently stored in a database. This interval-based binning helps in maintaining data integrity and facilitates easier access and analysis of the data stored, particularly when dealing with the large volumes of data typical in sensory applications like odor detection.

3.6 General Model of Sensing System

Below is a straightforward diagram of an odor-sensing system. In this system, an array of sensors detects the odor, which is then processed and identified using an artificial neural network algorithm. This method allows for the effective recognition of specific odors based on the sensor data analyzed by the neural network.

3.7 Data Acquisition

In the proposed methodology, data acquisition is illustrated through an array of sensors, as shown in Figure 2. This visual representation helps clarify the process and layout of the sensor array involved in collecting the data [65].

Figure 2: Sensor Array

The diagram above displays how Volatile Organic Compounds (VOCs) are emitted from human hands and detected by an array of sensors. When the hand comes into contact with the sensor array, the heaters within the sensors react with the VOCs emitted from the skin. Each sensor, depending on its specific capabilities, detects different VOCs as illustrated in Figure 3. The sensors capture data in the form of analog signals. These signals are then passed through a microcontroller that converts them into digital form. Due to the continuous nature of the data transmission, only the data collected over a five-second interval is recorded and presented in the table below. This approach ensures manageable and relevant data collection for further analysis.

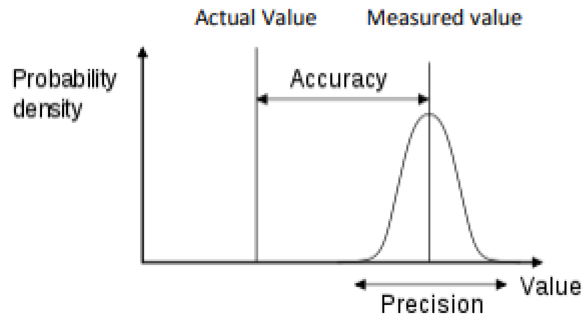

Figure 3: Shows the accuracy graph

3.8 Analyzer of ECG

The ECG Analyzer described in the proposed methodology employs a complex architecture designed to analyze electrocardiogram data effectively. This system processes ECG signals to identify potential cardiac abnormalities using advanced computational techniques, ensuring accurate and dependable diagnostics. The analysis conducted by this system includes evaluating heart rhythms, as depicted in Figure 4, identifying arrhythmias, and detecting other cardiovascular conditions. Such comprehensive analysis aids clinicians in making well-informed decisions regarding patient care, enhancing the overall treatment process.

Figure 4: ECG Analyzer

3.9 Architecture

Following is the architecture of the training model shown in Figure 5.

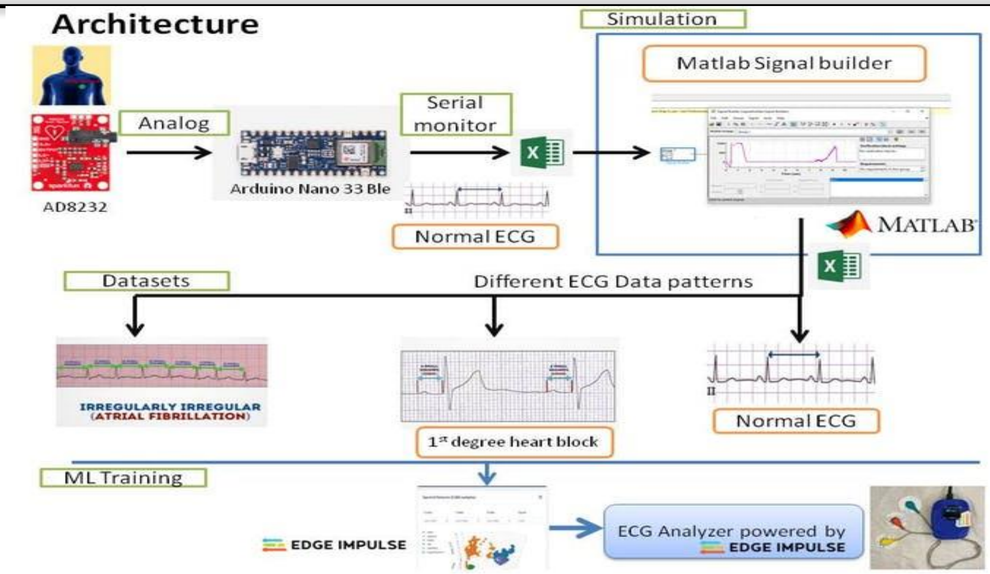

Figure 5: Architecture

4. Result Analysis

The effectiveness of the proposed method is evaluated by comparing it with findings from previous studies. One such study [19] introduced an automatic diagnosis system for the 12-lead ECG, employing a deep neural network that achieved an accuracy of 80%. The current method [39] similarly utilizes deep neural networks, but leverages data from the Telehealth Network of Minas Gerais for enhanced accuracy.

Another related research developed a heart disease diagnosis system using a secure Internet of Health Things (IoHT) framework based on an auto encoder deep neural network [66]. This system used the PASCAL and PhysioNet datasets and achieved an accuracy of 91.9%. Additionally, a different study introduced a method for the early detection of coronary heart disease using the Naive Bayes algorithm [67], achieving an accuracy of 84.0714. This approach was notable for utilizing a self-generated dataset specific to the research [68]. Lastly, another researcher developed a smart healthcare monitoring system designed for heart disease prediction [69], which combined ensemble deep learning with feature fusion [70]. This system, utilizing datasets from Cleveland and Hungarian, reported a high accuracy rate of 98.5%, demonstrating its effectiveness in predicting heart disease shown in Table 1.

Table 1. Comparison of Experimental Results

Experiment No.	Subjects	Accuracy	No of Sensors used	Precision	Specificity	AUC
1	05	71.0000	10	0.3784	0.7125	0.7269
2	10	80.5000	10	0.3137	0.3137	0.8527
3	10	84.4000	6	0.3704	0.8489	0.8654
4	20	86.3000	10	0.2348	0.8679	0.8837
5	20	95.9000	10	0.5600	0.9653	0.9527

6. Conclusion

Biometric identification in wearable devices can effectively utilize human body odor as a unique identifier. In this system, an Arduino microcontroller converts analog signals into digital ones for authentication, and a neural network is used for pattern classification. The initial experiment involved ten sensors to collect data from five individuals, with each sensor operating independently during data acquisition. The results from this setup showed an accurate rate of 71%. Upon repeating the experiments with the same dataset, the average accuracy was recorded at 73±2%, and an increase in the dataset size improved the accuracy.

In a second experiment, the dataset was expanded to include ten individuals, with data acquisition conducted using sensor arrays. Each array processed data from all ten individuals, leading to improved accuracy documented at 80.5%, with an average accuracy of 80±2% after several repetitions of the experiment on the same datasets.

A third experiment used an array of six sensors, which further enhanced accuracy. The data, captured at various times from ten individuals, achieved an accuracy of 84.40%, with an average of 86±2% after multiple experimental repetitions. By increasing the number of samples to twenty and conducting multiple experiments on these, the accuracy predominantly remained at 86%, although it peaked at 95% in one instance, averaging out to 86%.

These findings suggest that while some odors were not consistently identified, others were recognized accurately, leading to an overall average accuracy of 86%. This indicates potential areas for improvement in sensor technology and data processing to enhance identification reliability.

7. Future work

Future work should focus on enhancing the accuracy of odor-sensing systems by improving the performance and sensitivity of the sensors. There is a critical need to increase sensor sensitivity to boost accuracy. A common issue affecting accuracy arises when individuals use deodorants, which can mask natural odors. To address this, there is a significant demand for a machine capable of distinguishing human odor regardless of deodorant use. This advanced system should effectively differentiate between human odors and other scents, ensuring reliable identification.

REFERENCES

1.Bottinger EP. Foundations, promises and uncertainties of personalized medicine. Mount Sinai Journal of Medicine: A Journal of Translational and Personalized Medicine: A Journal of Translational and Personalized Medicine. 2007;74(1):15-21.

2.Update A. Heart disease and stroke statistics–2017 update. Circulation. 2017;135:e146-e603.

3.Ullah H, Faran M, Batool Z, Nazir A, Gilanie G, Amin N. Diagnosis of Ocular Diseases Using Optical Coherence Tomography (OCT) at λ= 840 nm. Lasers in Engineering (Old City Publishing). 2022;53.

4.Iqbal MJ, Bajwa UI, Gilanie G, Iftikhar MA, Anwar MW. Automatic brain tumor segmentation from magnetic resonance images using superpixel-based approach. Multimedia Tools And Applications. 2022;81(27):38409-27.

5.Janjua HU, Andleeb F, Aftab S, Hussain F, Gilanie G. Classification of liver cirrhosis with statistical analysis of texture parameters. International Journal of Optical Sciences. 2017;3(2):18-25.

6.Lloyd-Jones DM. Cardiovascular risk prediction: basic concepts, current status, and future directions. Circulation. 2010;121(15):1768-77.

7.Afzal F, Ullah H, Amjad M, Akhtar M, Shah MI, Batool Z, et al. Detection of Uric Acid in UV-VIS wavelength Regime. JOURNAL OF NANOSCOPE (JN). 2023;4(1):75-81.

8.Ahmed M, Gilanie G, Ahsan M, Ullah H, Sheikh FA. Review of Artificial Intelligence-based COVID-19 Detection and A CNN-based Model to Detect Covid-19 from X-Rays and CT images. VFAST Transactions on Software Engineering. 2023;11(2):100-12.

9.Gilanie G. Spectroscopy of T2 weighted brain MR image for object extraction using prior anatomical knowledge based spectroscopic histogram analysis 2013.

10.Janjua HU, Jahangir A, Gilanie G. Classification of chronic kidney diseases with statistical analysis of textural parameters: a data mining technique. International Journal of Optical Sciences. 2018;4(1):1-7.

11.Ullah H, Batool A, Gilanie G. Classification of Brain Tumor with Statistical Analysis of Texture Parameter Using a Data Mining Technique. International Journal of Industrial Biotechnology and Biomaterials. 2018;4(2):22-36.

12. Ullah H, Batool Z, Nazir A, Akhtar U, Gilanie G, Rehman J, et al. Proteins and Triglycerides Measurement in Blood Under Ultraviolet (UV)/Visible (Vis) Spectroscopy at & lambda;= 190 to 1100 nm with an Additional He-Ne Laser Source. LASERS IN ENGINEERING. 2023;55(3-6):157-67.
13. Eilat-Adar S, Sinai T, Yosefy C, Henkin Y. Nutritional recommendations for cardiovascular disease prevention. Nutrients. 2013;5(9):3646-83.
14. Gilanie G, Saher A, Batool SN, Khursheed A, Shafique H, Perveen S, et al. Digital Image Processing for Ultrasound Images: A Comprehensive. Digital Image Processing. 2021;15(3).
15. Amjad M, Ullah H, Andleeb F, Batool Z, Nazir A, Gilanie G. Fourier-Transform Infrared Spectroscopy (FTIR) for Investigation of Human Carcinoma and Leukaemia. Lasers in Engineering (Old City Publishing). 2021;51.
16. Gilanie G, Ullah H, Mahmood M, Bajwa UI, Habib Z. Colored Representation of Brain Gray Scale MRI Images to potentially underscore the variability and sensitivity of images. Current Medical Imaging Reviews. 2018;14(4):555-60.
17. Hafeez HA, Elmagzoub MA, Abdullah NAB, Al Reshan MS, Gilanie G, Alyami S, et al. A CNN-model to classify low-grade and high-grade glioma from mri images. IEEE Access. 2023;11:46283-96.
18. Lupton D, Maslen S. Telemedicine and the senses: a review. Sociology of health & illness. 2017;39(8):1557-71.
19. Anwaar M, Gilanie G, Ahmad F, Sharif W, Shaheen M, Ashraf M, et al. Enhanced Relative Discrimination Criterion and RSS-ELM Techniques to Improve the Document Classification. 2024.
20. Ben-Zeev D. Mobile health for all: public-private partnerships can create a new mental health landscape. JMIR Mental Health. 2016;3(2):e5843.
21. Gilanie G, Bajwa UI, Waraich MM, Habib Z. Computer aided diagnosis of brain abnormalities using texture analysis of MRI images. International Journal of Imaging Systems and Technology. 2019;29(3):260-71.
22. Gilanie G, Bajwa UI, Waraich MM, Habib Z, Ullah H, Nasir M. Classification of normal and abnormal brain MRI slices using Gabor texture and support vector machines. Signal, Image and Video Processing. 2018;12:479-87.
23. Gilanie G, Batool SN, Khursheed A, Shafique H, Mahmood N, Cheema S, et al. Bit Pattern Selection Based Novel Method of Steganography in RGB Encoding Scheme Based Digital Images.
24. Batool SN, Yang J, Gilanie G, Latif A, Yasin S, Ikram A, et al. Forensic Radiology: A robust approach to biological profile estimation from bone image analysis using deep learning. Biomedical Signal Processing and Control. 2025;105:107661.
25. Gilanie G, Shafiq H, Batool SN, Abbas SN, Shafique H, Cheema S, et al. PARAMETER OPTIMIZATION OF AUTOENCODER FOR IMAGE CLASSIFICATION USING GENETIC ALGORITHM. Spectrum of Engineering Sciences. 2025;3(4):201-13.
26. Gilanie G, Cheema S, Latif A, Saher A, Ahsan M, Ullah H, et al. A Robust Method of Bipolar Mental Illness Detection from Facial Micro Expressions Using Machine Learning Methods. Intelligent Automation & Soft Computing. 2024;39(1).
27. Asghar K, Gilanie G, Saddique M, Habib Z. Automatic Enhancement Of Digital Images Using Cubic BÃ© zier Curve And Fourier Transformation. Malaysian Journal of Computer Science. 2017;30(4):300-10.
28. Asghar S, Gilanie G, Saddique M, Ullah H, Mohamed HG, Abbasi IA, et al. Water classification using convolutional neural network. IEEE Access. 2023;11:78601-12.

29.Attique M, Gilanie G, Mehmood MS, Naweed MS, Ikram M, Kamran JA, et al. Colorization and automated segmentation of human T2 MR brain images for characterization of soft tissues. PloS one. 2012;7(3):e33616.
30.Bajwa UI, Shah AA, Anwar MW, Gilanie G, Ejaz Bajwa A. Computer-aided detection (CADe) system for detection of malignant lung nodules in CT slices-a key for early lung cancer detection. Current Medical Imaging. 2018;14(3):422-9.
31.Baranowski J, Piątek P. Fractional band-pass filters: design, implementation and application to EEG signal processing. Journal of Circuits, Systems and Computers. 2017;26(11):1750170.
32.Gilanie G, Rehman N, Bajwa UI, Sharif S, Ullah H, Mushtaq MF, editors. FERNet: A Convolutional Neural Networks Based Robust Model to Recognize Human Facial Expressions. International Conference on Soft Computing and Data Mining; 2022: Springer.
33.Gilanie G, Bajwa UI, Waraich MM, Habib Z. Automated and reliable brain radiology with texture analysis of magnetic resonance imaging and cross datasets validation. International Journal of Imaging Systems and Technology. 2019;29(4):531-8.
34.Ali F, El-Sappagh S, Islam SR, Kwak D, Ali A, Imran M, et al. A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion. Information Fusion. 2020;63:208-22.
35.Gilanie G, Javedb M, Rauf B, Cheemaa S, Latif A, Perveena S, et al. RiceAgeNet: Age Estimation of Pakistani Grown Rice Seeds using Convolutional Neural Networks.
36.Gilanie G, Nasir N, Bajwa UI, Ullah H. RiceNet: convolutional neural networks-based model to classify Pakistani grown rice seed types. Multimedia Systems. 2021:1-9.
37.Gilanie G, Batool SN, Abbas SN, Shafique H, Iqbal M, Cheema S, et al. READABLE TEXT RETRIEVAL FROM NOISE-INFLUENCED DOCUMENTS USING IMAGE RESTORATION METHODS. Spectrum of Engineering Sciences. 2025;3(3):337-60.
38.ULLAH H, BATOOL Z, NAZIR A, AHMED K, RASHEED M, AL-KHATTAF FS, et al. Potential application of CeO2/Au nanoparticles as contrast agents in optical coherence tomography. Journal of Optoelectronics and Advanced Materials. 2024;26(July-August 2024):307-15.
39.Yaseen M, Khurshed A, Ullah H, Batool Z, Nazir A, Gilanie G, et al. In-vitro Evaluation of Anticancer Activity of Rhodamine-640 perchlorate on Rhabdomyosarcoma cell line. 2022.
40.Gilanie G, Batool SN, Abbas SN, Latif A, Iqbal M, Shafique H, et al. STEGANOGRAPHIC SECRET COMMUNICATION USING RGB PIXEL ENCODING AND CRYPTOGRAPHIC SECURITY. Spectrum of Engineering Sciences. 2025;3(3):323-36.
41.Ribeiro AH, Ribeiro MH, Paixão GM, Oliveira DM, Gomes PR, Canazart JA, et al. Automatic diagnosis of the 12-lead ECG using a deep neural network. Nature communications. 2020;11(1):1760.
42.Khera EA, Ullah H, Hussain F, Abubakar S, Majeed A, Tabssum I, et al. Characterization of Nickel Oxide Thin Films for Smart Window Energy Conversion Applications: Comprehensive Experimental and Computational Study. Available at SSRN 4235112.
43.Ullah H, Batool Z, Nazir A, Mohsin S, Raouf A, Rasheed M, et al. Assessing Graphene Oxide (GO) and CuO Nanocomposites for Effective Antibacterial Properties Using Laser Interferometry. Lasers in Engineering (Old City Publishing). 2023;55.

44.Rubab SF, Mushtaq MF, Tahir MH, Amna, Samad A, Gilanie G, et al., editors. The Comparative Performance of Machine Learning Models for COVID-19 Sentiment Analysis. International Conference on Soft Computing and Data Mining; 2022: Springer.

45.ULLAH H, GHALIB A, AKHTAR M, MEHMOOD R, AKRAM A, BATOOL Z, et al. Measurements of Hyperproteinaemia in Human Blood Using Laser Interferometry: In Vitro Study. Lasers in Engineering (Old City Publishing). 2024;57.

46.Ullah H, Gilanie G, Attique M, Hamza M, Ikram M. M-mode swept source optical coherence tomography for quantification of salt concentration in blood: an in vitro study. Laser Physics. 2012;22:1002-10.

47.Sajid M, Sharif W, Gilanie G, Mazher M, Iqbal K, Akhtar MA, et al. IoMT-Enabled Noninvasive Lungs Disease Detection and Classification Using Deep Learning-Based Analysis of Lungs Sounds. International Journal of Advanced Computer Science & Applications. 2025;16(2).

48.Krithiga B, Sabari P, Jayasri I, Anjali I, editors. Early detection of coronary heart disease by using naive bayes algorithm. Journal of Physics: Conference Series; 2021: IOP Publishing.

49.Ghaffar AA, Mushtaq MF, Amna, Akram U, Samad A, Gilanie G, et al., editors. Refined Sentiment Analysis by Ensembling Technique of Stacking Classifier. International Conference on Soft Computing and Data Mining; 2022: Springer.

50.Ullah H, Gilanie G, Hussain F, Ahmad E. Autocorrelation optical coherence tomography for glucose quantification in blood. Laser Physics Letters. 2015;12(12):125602.

51.Wazir E, Gilanie G, Rehman N, Ullah H, Mushtaq MF, editors. Early Stage Detection of Cardiac Related Diseases by Using Artificial Neural Network. International Conference on Soft Computing and Data Mining; 2022: Springer.

52.Ullah H, Zafar M, Batool Z, Nazir A, Gilanie G, Rehman J. Early Detection of Liver, Ovary, Breast and Stomach Tumours in the Visible (λ= 630 nm) and Infrared (IR)(λ= 10.5 to 5.5 μm) Wavelength Regimes. Lasers in Engineering (Old City Publishing). 2023;54.

53.Akkaş MA, Sokullu R, Çetin HE. Healthcare and patient monitoring using IoT. Internet of Things. 2020;11:100173.

54.Gilanie G, Batool SN, Abbas SN, Cheema S, Latif A, Shafique H, et al. DEEP LEARNING-BASED APPROACH FOR ESTIMATING THE AGE OF PAKISTANI-GROWN RICE SEEDS. Spectrum of Engineering Sciences. 2025;3(1):557-72.

55.Gilanie G. Automated Detection and Classification of Brain Tumor from MRI Images using Machine Learning Methods: Department of Computer Science, COMSATS University Islamabad, Lahore campus; 2019.

56.Gilanie G, Attique M, Naweed S, Ahmed E, Ikram M. Object extraction from T2 weighted brain MR image using histogram based gradient calculation. Pattern Recognition Letters. 2013;34(12):1356-63.

57.Gilanie G, Bajwa UI, Waraich MM, Asghar M, Kousar R, Kashif A, et al. Coronavirus (COVID-19) detection from chest radiology images using convolutional neural networks. Biomedical Signal Processing and Control. 2021;66:102490.

58. Batool SN, Gilanie G. CVIP-Net: A Convolutional Neural Network-Based Model for Forensic Radiology Image Classification. Computers, Materials & Continua. 2023;74(1).

59. Gilanie G, Bajwa UI, Waraich MM, Anwar MW. Risk-free WHO grading of astrocytoma using convolutional neural networks from MRI images. Multimedia Tools and Applications. 2021;80(3):4295-306.
60.Gilanie G, Bajwa UI, Waraich MM, Anwar MW, Ullah H. An automated and risk free WHO grading of glioma from MRI images using CNN. Multimedia tools and applications. 2023;82(2):2857-69.
61.Gilanie G, Batool SN, Shafique H, Khursheed A, Mahmood N, Cheema S, et al. An Overview on X-Rays ImagesProcessing: Methods, Challenges& Issues, and Future Work.
62.Nazir A, Ullah H, Gilanie G, Ahmad S, Batool Z, Gadhi A. Exploring Breast Cancer Texture Analysis through Multilayer Neural Networks. Scientific Inquiry and Review. 2023;7(3):32-47.
63.Malik S, Ullah H, Andleeb F, Batool Z, Nazir A, Gilanie G, et al. Enhancing Contrast in Optical Imaging of Cancer tissues and Study the Spectral Properties of Methylene Blue. Acta Microscópica. 2021;30(2):49-57.
64.Siddique MA, Akhtar M, Majid MA, Khera EA, Ahmad M, Gilanie G, et al. A Multi-Modal Approach for Exploring Sarcoma and Carcinoma Using FTIR and Polarimetric Analysis. Microscopy Research and Technique. 2025.
65.Rashid MS, Gilanie G, Naveed S, Cheema S, Sajid M. Automated detection and classification of psoriasis types using deep neural networks from dermatology images. Signal, Image and Video Processing. 2024;18(1):163-72.
66.Rafiq M, Bajwa UI, Gilanie G, Anwar W. Reconstruction of scene using corneal reflection. Multimedia Tools and Applications. 2021;80(14):21363-79.
67.Naveed S, Husnain M, Alsubaie N, Samad A, Ikram A, Afreen H, et al. Drug efficacy recommendation system of glioblastoma (GBM) using deep learning. IEEE Access. 2024.
68.Ghani M, Gilanie G. The IOMT-Based Risk-Free Approach to Lung Disorders Detection from Exhaled Breath Examination. INTELLIGENT AUTOMATION AND SOFT COMPUTING. 2023;36(3):2835-47.
69.Khera EA, Ullah H, Hussain F, Abubakar S, Majeed A, Tabssum I, et al. Characterizing nickel oxide thin films for smart window energy conversion applications: Combined experimental and theoretical analyses. ChemistrySelect. 2023;8(37):e202302320.
70.Shafiq H, Gilanie G, Sajid M, Ahsan M. Dental radiology: a convolutional neural network-based approach to detect dental disorders from dental images in a real-time environment. Multimedia Systems. 2023;29(6):3179-91.

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