

## Advanced cardiac health monitoring system

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**Abstract** - The rising global burden of cardiovascular diseases (CVDs) underscores an ever-growing need for real-time, accurate, and user-friendly cardiac monitoring systems as an effective preventative measure for early diagnosis and treatments. It also proposes a novel model of cardiac health monitoring system using an ESP32 microcontroller along with blood pressure and ECG sensing technologies. In order to reduce noise and motion artifact, the system first harvested cardiac signals via ECG electrodes. This stage amplifies and filters these signals. Store Data: Upload processed data to an online repository for analysis Using feature extraction and machine learning algorithms, the system is able to generalize multiple cardiac conditions but not limited to Normal rhythm, Premature Ventricular Contractions (PVC), Right Bundle Branch Block (RBBB), Left Bundle Branch Block (LBBB). The mobile application interface acts as an extra part of the architecture that easily relays the diagnostic results to family and health professionals. This feedback loop facilitates continuous monitoring of patients outside of traditional clinical settings with the potential for improving remote patient management and timely alerting. Modern infrastructural support for modern cardiac healthcare: such as the integration of sensing, wearable technologies, mobile communication, and intelligent diagnosis in the cloud. The system combines clinical-grade monitoring with consumer-grade wearable.

**Key Words:** CardiacHealthMonitoring,Electrocardiogram (ECG), Blood Pressure Sensor, Wearable Health Devices, Internet of Things (IoT), Machine Learning Algorithms, ESP8266 Microcontroller, Real-time Health Diagnosis, Remote Patient Monitoring Systems, Advanced Healthcare Technology.

### 1. INTRODUCTION

According to WHO, CVDs continue to be one of the most troublesome problems of global health, causing 17.9 million deaths a year. This is a heartbreaking number that highlights the need for effective, constant, and seamless cardiac health monitoring platforms. In general, the prevention of MI, arrhythmias, HF by hypertension and other CVDs involve comprehensive monitoring and early detection of all processes related to cardiac function. BP measurement and electrocardiography (ECG) have long been of great significance in cardiology as routine diagnostic procedures. The ECG has been utilized for over 70 years as one of the major diagnostic instruments used in the assessment of electrical function of the heart for pathology tailors and failures such as ischemia or arrhythmias. Furthermore, blood pressure is a mainstay of clinical assessment of cardiovascular health, especially for atherosclerosis and hypertension. But both conventional ways of tracking ECG and blood pressure are limitedly used for clinical settings, where they can only be operated in specified intervals. Clinically important, worrisome symptoms that arise between visits may therefore go undetected — particularly among patients with intermittent. Advancements in wearable electronics, wireless communication systems, and algorithms of machine learning (ML) have transformed intelligent health monitoring systems that can be automated into reality. These systems attempt to combat many of these limitations. Today, with the integration of biosensors and IOT (Internet of Things) linked wearable, cardiac health parameters can be monitored continuously and in real time without going to the patients. These developments increase patient compliance and engagement, but also equip physicians with timely data to make improved clinical decisions. But commercial wearable technologies such as fitness analysis and smart watches;

references basic parameters such as heart rate and step counting, therefore, there is no considerable change in such devices Functionalities, which is a tremendous differentiator. In addition to this, diagnostic capabilities are minimal, if at all. Furthermore, these devices rarely have shall we say the technical accuracy and reproducibility to be able to clinically substantiate the diagnosis of complex cardiovascular disorders. Additionally, these devices predominantly utilize single-lead electrocardiograms (ECGs), thereby restricting the reach of diagnostic accuracy in terms of advanced atypical atrial block, such as Left Bundle Branch Block (LBBB), Right Bundle Branch Block (RBBB), and Ventricular Premature Contractions (PVCs). Furthermore, many of the systems are constrained by power requirements and signal artifacts and lack integrated diagnostic algorithms. Novel cardiac health monitoring system integrated with ML classification, Edge computing with ESP8266 and high fidelity bio signal acquisition (ECG, blood pressure)Advanced Cloud-Based Analytics In addition to the radio-less collection and transmission of heart signals, machine learning models assist the proposed system in achieving real-time intelligent diagnosis. Such an approach reduces the hospital readmission rates, increases the likelihood of spotting anomalies at an early stadium and makes timely alerts possible to the relevant stakeholders like family members and clinicians. It improves the system's structure with a mobile application that promotes user interaction and engagement. These signal preprocessing, feature extraction, classification, cloud storage, and real-time reporting modules are combined in the complete, end-to-end solution for remote cardiac care. As heart diseases become more common and demand for personalized care increases, the advancement of wearable intelligent cardiac monitoring systems has great potential in the future of digital health. The string galvanometer, developed by Willem Einthoven, offered the first practical means of recording electrical activity in the human heart, and certified the monitoring of cardiac function in the early 1900s. He was awarded the Nobel Prize in Medicine in 1924 for the invention of the Electrocardiograph (ECG). This invention literally paved the way for clinical electrophysiology. Large, unwieldy and limited in use to the lab, Einthoven's early ECG systems represented an unparalleled leap forward in the diagnosis of cardiovascular disease. In the subsequent decades there were incremental refinements to ECG systems. Towards the middle of the 20th century, the introduction of small portable ECG machines to be used in the clinical setting greatly improved diagnostic performance. However, the biggest advancement came in the 1980s and 1990s with the

development of the Halter monitor, a portable battery-powered device that could record your heart rhythms around the clock for 24 to 48 hours. At least these were valuable for obtaining ECG traces during everyday life and amplifying sporadic arrhythmias. Event recorders also known as loop recorders, which provided further extended monitoring with the ability for patients to record symptoms at the time of occurrence with a push of a button thus allowing correlation real-time monitoring system. The design of this wearable enables it to monitor several physiological parameters, such as body temperature, blood pressure, and ECG signals. In addition, this makes fall detection easier, especially for elderly or high-risk patients. The architecture of a system consists of three modules including a software module in which cloud-based machine learning is embedded, a data processing module in which signal amplification, filtering, and analog-to-digital conversion take place, and, a hardware module consisting of microcontrollers and biomedical sensors. Various electrodes for ECG and blood pressure are embedded into a flexible and wearable chest strap forming the hardware system. These sensors receive real-time signals from the human body and record critical information including heart rhythm (Electrocardiogram), systolic and diastolic blood pressure, and core temperature. The raw analog signals are then preprocessed through electronic circuits that amplify and filter the signals to remove noise and motion artifacts. After cleaning, the signals are converted to digital and sent to a Wi-Fi-enabled microcontroller (ESP8266 or NodeMCU) to transfer the data confidentially. After transmission, the data is processed on a centralized cloud server that is equipped with cutting-edge machine learning algorithms. Some examples of these would be Bundle Branch Blocks (RBBB, LBBB), Premature Ventricular Contractions (PVCs), and erratic patterns in blood pressure trends. Electrocardiography (ECG), the most widespread diagnostic technique for the heart, allows trained cardiologists to identify numerous conditions from studying patterns in the waveform. In contrast, conventional ECG recordings are quick snapshots that may not capture anomalies such as arrhythmias or conduction blocks. These shortcomings are addressed by continuous monitoring systems, like Halter monitors, which are usually less spatially-resolved and employ fewer leads. Additionally, traditional ECG devices are weighty and power-dependent, limiting mobility and reducing real-time responsiveness of patients. These area newer trends have come up based on wearable technology and wireless sensor networks. Cardiovascular diseases are still one of the most notorious major health problems and any tardy detection and treatment

of cardiac problems may cause severe fatalities and high morbidity, hence continuous ECG monitoring is the mechanism that composes a great accessory for the detection of the critical ECG signals. Manual analysis of the ECG signals is still laborious and subject to human error even under the ambient noise. After exploring and successfully implementing machine learning (ML) models (Decision Tree (DT), Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM) and Random Forest (RF)), a number of recent studies have demonstrated that RF produced the highest accuracy (98%) in classifying data (Subba and Chingtham, 2024). Previous methods are strongly weighted towards feature extraction, utilizing wavelet transforms and FFTs to uncover hidden patterns in the signal. Although effective, these techniques are resource-intensive and face challenges such as noise and imbalance in the unusually rare cases of arrhythmias such as Ventricular Ectopic Beat (VEB) and Supraventricular Ectopic Beat (SVEB). We propose a system using a combination of ECG and blood pressure sensors built into a chest strap, combining real-time signal acquisition with cloud-based machine learning-based signal analysis. In contrast to previous techniques, continuous tracking of the patient through IoT connectivity is the main focus of our architecture, where the data obtained is sent to the cloud to be analyzed by ML models. Signal processing refers to the transformation of data into a form similar to the signals used in clinical diagnostics, such as de-noising and normalization, improving their quality and clarity, which aids in more reliable diagnostics. The system architecture facilitates remote access to data and notifications for medical staff and family members, thus overcoming constraints of conventional offline mechanisms. The subsequent sections present various details about the hardware components, signal processing flow, ML algorithm integration, and performance evaluation.

### 1.1 HEART AUSCULTATION

The acquisition of heart signals via electrocardiography (ECG) forms the backbone of modern cardiac diagnostics and monitoring. The heart generates electrical impulses that correspond to the depolarization and repolarization of the muscle tissue within the heart and the ECG is a recording of these impulses represented as a series of waveform patterns. The useful properties of these waveforms, when acquired, filtered, and analyzed correctly, are important determinants of cardiac rhythm, conduction pathways, and structural integrity. The bio potential differences generated by the heart's electrical activity are detected through electrodes placed on the surface of the skin. These raw signals are low

amplitude signals and are also affected by muscle activities in the surrounding area and environmental noise, requiring pre-processing circuits such as amplifiers and filters before being analyzed. The collected ECG waveform corresponds to a single cardiac cycle and consists of unique characteristics such as the P wave, the QRS complex, the T wave, and related intervals (PR, ST, QT). The P wave represents the depolarization of the atria that is initiated by the Sino atrial (SA) node, which results in atrial contraction to prepare the ventricles to receive blood. The P wave, normal upright in most leads, is the first insight into a functioning atrial rhythm. The PR interval begins at the beginning of the P wave and ends at the start of the Q wave, immediately following this. This period is termed the delay in impulse conduction through the atrioventricular (AV) node and is usually 120 to 200 milliseconds. Changes in this interval can suggest AV block or pre-excitation syndromes. The QRS complex represents the depolarization of the ventricular myocardium and is the largest component of the ECG. Because the ventricles have more muscle mass, this wave has a greater amplitude and sharper morphology when compared to the P wave. A normal QRS duration is between 60 - 100 ms; abnormal values may indicate a conduction defect (e.g. bundle-branch blocks) or ventricular hypertrophy. The region of ST segment follows the QRS complex, indicating the time from ventricular depolarization to repolarization. It usually parallel the isoelectric line and is < 0.12 seconds. ST segment elevation or depression serves as important indicators of myocardial ischemia or infarction and plays a crucial role in emergency cardiac diagnosis. The electrocardiographic T wave reflects ventricular repolarization, during which the T wave is usually wider than the preceding QRS complex and of smaller amplitude because of the asynchronous nature of this phase. It usually is upright and kills in less than 0.20 sec. T-wave abnormalities—such as T-wave inversion or flattening—may reflect myocardial strain, electrolyte imbalance, or ischemia. QT Interval: The time period between the onsets of the Q wave to the end of the T wave, representing both ventricular depolarization and repolarization. The normal QT interval is about 0.38 seconds and needs to be corrected for heart rate etc using formulas such as Bazett's equation. QT interval: The prolonged QT interval (e.g., caused by antiarrhythmic drugs) leads to a higher risk of arrhythmias (e.g., Torsade's de Pointes); The shortened QT interval may indicate hyperkalemia or drug effects. The ECG waveform includes P wave, QRS complex, and T wave and each component provides vital information regarding the diagnosis of cardiac pathologies. Atrial fib, for example, has no distinct P waves

and an irregularly irregular rhythm. The typical presentation of ventricular tachycardia is a widened QRS complex with a rapid rate. ST segment depressions and T wave inversions can also indicate myocardial ischemia or infarction. Thus, precise measurement and interpretation of these electrical recordings are crucial for patient management. As digital health technologies have evolved, so has ECG acquisition from clinical settings to wearable that can monitor continuously. They leverage high precision analog front end devices, such as the AD8232 ECG sensor, to extract and process signals from the body collaborate with chest straps or smart clothing. A microcontroller device used (e.g., NodeMCU or ESP32) amplifies, filters, and digitizes these signals before wirelessly sending them to cloud-based servers. The rest happens in the cloud, where the machine learning algorithms read this data and draws features such as R-R intervals, QRS duration, and ST segment morphology. Using those features, we train and validate classification models proficient in identifying arrhythmias, conduction delays, and ischemic patterns with high precision. It provides the basis for next-gen, intelligent cardiac monitoring systems; while traditional ECG morphology are used in this context The ultimate added value comes from the integration of IOT and AI technologies that offers real-time diagnostics and remote health management, which turns the classical ECG from a static diagnostic tool into a dynamic, predictive and personalized monitoring system

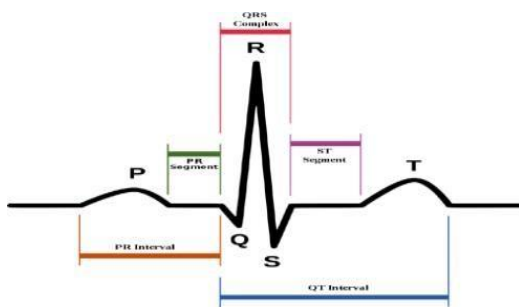


Fig 1: Components of a Standard ECG Waveform

## 1.2 SYSTEM DESIGN AND IMPLEMENTATION

### A. SYSTEM DESIGN

The designed and implemented cardiac health monitoring system has been developed as a wearable format targeting accurate, real-time, and remote monitoring of heart diseases. Its system architecture consists of physiological sensors, IOT-based microcontrollers, cloud storage, and machine learning algorithms. These components work together to enable

reliable and timely acquisition, processing, and interpretation of cardiac signals so that doctors can respond quickly when needed. Cardiovascular diseases (CVDs) remain the leading cause of death worldwide, largely due to limited early detection tools and real-time monitoring options. Tools like Halter monitors and ECG machines aren't always accessible at home and typically don't offer advanced diagnostic capabilities. Wearable devices such as smart watches usually capture only basic metrics, often with low signal accuracy, limited sensor configurations, and no real-time communication with healthcare providers. To tackle these challenges, this project introduces a chest strap wearable solution that records both electrical (ECG) and pressure-based cardiovascular data, processes it with advanced algorithms, and shares the results with healthcare providers and family through a cloud-based platform. The hardware of this system is engineered for high-fidelity signal capture and energy-efficient performance, with the ESP8266 NodeMCU microcontroller serving as the core component due to its built-in Wi-Fi capabilities that enable IOT connectivity. The key hardware components include the AD8232 ECG sensor, a low-power analog front-end that filters and amplifies ECG signals for accurate waveform reconstruction, and the LM35 temperature sensor, which monitors real-time skin temperature to aid in contextual diagnosis. Additionally, the DHT11 sensor records ambient temperature and humidity, factors that can influence physiological readings. To further improve signal integrity, amplifier and filter circuits are used to eliminate motion artifacts and reduce noise. An LCD display is included to provide real-time feedback to the user. All these components were physically assembled and programmed using the Arduino IDE, ensuring accurate, synchronized data acquisition and processing. Before assembling the physical system, the complete circuit was designed and tested virtually using Proteus Design Suite. This stage was crucial to confirm the expected behavior of the circuit, sensor integration, and consistent data flow from sensors to microcontroller to display. Simulations also covered analog-to-digital conversions and microcontroller logic. The NodeMCU ESP8266 was programmed in C++ to transmit real-time physiological data to the cloud. Sensor readings are collected at fixed intervals, locally processed to minimize noise, and securely transmitted to a cloud server using MQTT or HTTP protocols. This configuration supports continuous monitoring, remote access for healthcare providers, and the storage of historical data in the cloud for long-term analysis. For diagnostic purposes, the system leverages machine learning models hosted on the cloud server to identify complex cardiovascular conditions.





Fig 5. AD8232 sensor

The ECG signals obtained from electrodes attached to the chest are quite low in amplitude; hence they are amplified with the use of AD8232, which as an end result provides a clean analog output. The AD8232 is powered through the ESP32's 3.3V pin and both devices are connected to a common ground in this setup. The conditioned ECG signal is then fed into the first analog input (A0) of ESP32 to digitize the analog signal. The LO+ and LO- pins check that electrodes are connected for proper signal acquisition, and the SDN pin is left unconnected, which should leave the chip running. This configuration allows powerful real-time ECG data collection and transmission in m-health applications.

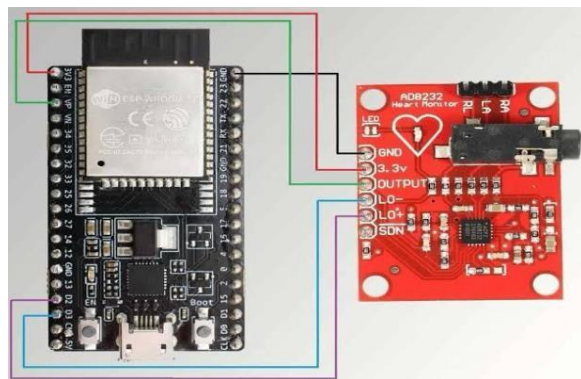


Fig 6. Connection of AD8232

Blood Pressure Sensor (Simulated using DHT Sensor)  
 Current design uses a DHT (used for temperature and humidity) as sensor, simulates blood pressure with early development stage. In the final version, it will be substituted with a real-time blood pressure sensor (i.e., MPX series or cuff-based system). The sensor plays an essential part in measuring systolic and diastolic values responsible for

cardiovascular load. The DHT sensor is just a placeholder, but it does show the modularity of the system and how easy it would be to integrate better pressure measuring hardware in the next revisions.

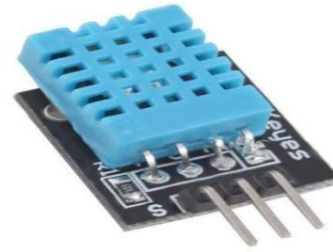


Fig 7 : DHT sensor

The communication between the ESP8266 NodeMCU microcontroller and a DHT11 digital temperature and humidity sensor — a key component towards incorporating environmental parameters in wearable health systems. With this arrangement, the sensor is powered by the 3.3V output of the NodeMCU connected to the VCC pin, while the common ground is connected to the GND pin of the sensor. The DHT11 signal (Data) pin is connected to a digital I/O pin of the NodeMCU (D4 in this case) that actually reads the data output of the sensor. Such protocols clean up wiring and efficiently transfer temperature and humidity data when only a single wire is used for communication. Including a DHT11 increases the context-awareness of the cardiac monitoring system, which can now correlate the environmental factors with the physiological parameters, enriching the health analytics.

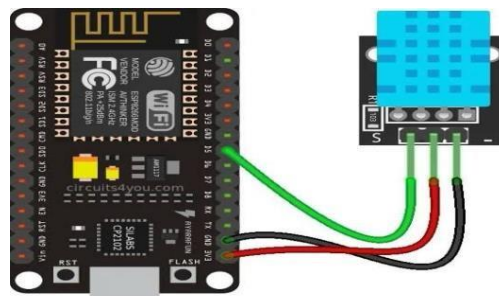


Fig 8 : DHT sensor connection

Temperature Sensor (LM35) LM35 sensor gives an output voltage proportional to body temperature in Celsius. It reflects key indicators of patients' physiological status, especially coupled with cardiovascular metrics. The LM35 provides an additional contextual layer of health data in this setup. The easy interfacing with NodeMCU and analog output helps to monitor not only cardiac functionalities but also vital signs strengthening the diagnostic model in febrile conditions when heart performance is influenced. Power Supply to guarantee continuous operation of the wearable device, a power supply system is arranged. These features cater for regulated 3.3V/5V DC sources via USB or lithium-ion batteries, providing both portable and stationary application. The ADC requires stable voltage levels to ensure accurate analog readings, while power to the communication module is essential for reliable data transmission. It ideally suits for continuous, real-time monitoring where power-saving techniques in the form of sleep modes and power-efficient regulators are adopted for improved battery life. At the heart of this system is the NodeMCU (ESP8266), a versatile microcontroller unit (MCU), which takes care of connecting to sensors and establishing wireless communication. Its integrated Wi-Fi lets it work well for Internet-of-Things (IOT) use cases, seamlessly connecting continually monitored physiological metrics to cloud services for reproducible sharing. It basically receives analog signals from the ECG and temperature sensors, digitizes them, and sends the data to the cloud in this project. Its compact nature, low power consumption, and strong cloud integration capabilities have made it a key cloud element in wearable biomedical applications.

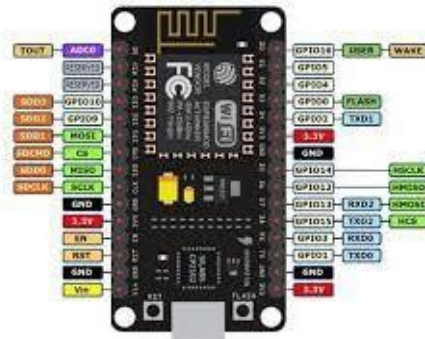


Fig 9: Node MCU Module

Microcontroller (ESP32/ESP8266 NodeMCU): This is the main processing unit that collects data from sensors and controls outputs such as displays. The ESP8266 uses pin names such as D1, D2, etc. (unlike ESP32, which uses GPIO numbers). VCC PIN: Connected to 3.3V from ESP8266; Ground Pin: common ground. The data pin is connected to D2 (GPIO4), we use a digital I/O pin for one-wire communication. This sensor provides ambient temperature and humidity, and this allows for the cross-referencing of environmental and physiological data. - AD8232 Heart Rate Monitor: This Module uses the 3.3V and GND pins of the ESP8266 for power supply, and the analog OUTPUT pin of the module is connected to A0 for transmission of the ECG signal. It tracks the heart's electrical activity for health monitoring. I2C LCD Display (16x2): Receives power from 3.3V and GND and uses the I2C interface for communication Typically, SDA and SCL pins are connected to GPIO4 (D2) and GPIO5 (D1). These show sensor output alongside temperature, humidity, and heart rate. All components commonly referenced to an identical ground. Use of a single-wire interface for the DHT11 reduces wiring. Analog ECG Signal: The AD8232 provides an analog ECG signal to facilitate accurate cardiac monitoring. Because the LCD uses I2C, this saves I/O, allowing you to add more modules.

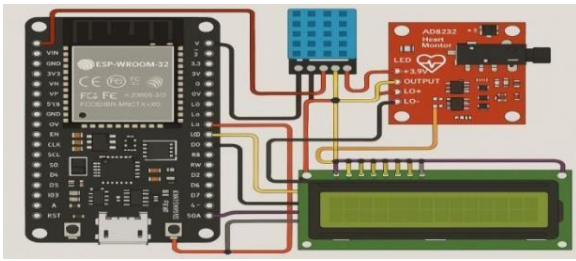


Fig 10 :Connection of electronic component.

The capabilities of NodeMCU (ESP8266), this wearable cardiac health checking system combines a set of sensors and smart modules, delivering a small footprint, real-time, and cloud-based functionality for on-demand cardiovascular information monitoring. From data acquisition through ECG electrodes and temperature sensors to complex signal processing, feature extraction, and machine learning-based diagnosis, everything is crafted to achieve accuracy, mobility, and accessibility to the user. Its modularity, validated by integration of both simulated and real world sensors, synergistic power control, and cloud integration position it as an ideal platform for scalable telemedicine applications and early disease detection in remote or resource constrained environments.

### C. APPLICATION INTERFACE

The application interface in a wireless ECG-based wearable cardiac healthcare system enables real-time data acquisition, analysis, and reporting using Arduino IDE, Google Colab and Pytorch for cloud machine learning and Blynk for mobile and IOT interface deployment. The programming of the microcontroller is developed using the IDE 'Arduino'. It's an open-source environment with an intuitive text editor, message area; toolbar with the most frequently used functions and a serial monitor. It is employed to program, compile, and download an embedded C code developed for the Arduino UNO board that is in charge of the signal acquisition of sensors (i.e., ECG electrodes, blood pressure sensors, and thermistors). The code sent to the Arduino UNO accomplishes several functions: setting up the sensor pins, reading analog values, applying some elementary signal processing (e.g., moving average filtering), and transferring the digitized data over UART to the IoT module. It also allows the use of external libraries used by the sensor drivers and the IoT communication protocol (for example, SoftwareSerial.h

for serial and BlynkSimpleSIM800.h for GSM module integration). The Arduino IDE's Serial Monitor offers an invaluable debugging tool by showing current sensor values in real time, assisting engineers in confirming system health and level of communication prior to cloud upload. In addition, the IDE can receive continuous firmware updates, so the system can be easily updated to add a new sensor or new algorithm in the future. For remote access and ease of use, Blynk is included as the mobile interface. Blynk is a versatile IOT cross-platform app that developers can use to build powerful smartphone dashboards without any advanced app developing skills. On Blynk, caregivers and patients can see live cardiovascular data - heart rate, electrocardiogram (ECG) waveform, as well as alerts for abnormal readings. Blynk is built around a layered architecture, which allows developers to move their hardware freely and have real communication real-time visualization easily from the smartphone. The top layer is the Blynk App, available on both iOS and Android, which enables users to create custom dashboards that they can control with a drag and drop editor. Users may also include, for example, interactive widgets such as graphs for tracking ECG waveforms, loudspeakers for heart rate alerts, LEDs for status monitoring, and notification modules for immediate alarms on the abnormal signal. The second layer, the Blynk Server, is the middleman between the hardware (Arduino UNO integrated with GSM module) and the smartphone. It handles core backend services such as data delivery, user authentication, and packet/session management to provide secure and reliable communication. The Blynk Library, the third layer, is placed on the Arduino microcontroller. This library in association with the Arduino board makes it easy to connect to the Blynk server through GSM or Wi-Fi and transmit data live to the user's mobile device. The above three parts form a complete system with synthetic functions and support the real-time monitoring function, rapid diagnosis function, and user-friendly application function of the entire cardiac system and are greatly useful for the management of cardiac health. The GSM-based IoT module (e.g., SIM800L) in the current approach links the Arduino to the Blynk cloud server and streams the live health data to the app periodically. Alerts can be set up using Blynk's eventer and notification widgets, allowing caregivers to receive instantaneous alerts if heart rate exceeds set levels, or if abnormal ECG patterns are detected. Having this level of interaction in real-time makes the device a lot more useful in both clinical and personal

settings. As soon as the digitized physiological signals are sent to the cloud, a superior machine-learning model performs the diagnosis and prediction processing. Google Colab is used to create, train and execute all of these machine learning models as it is accessible, has a strong computational backend, and also comes with GPU support. It offers an interface similar to Google Colab's, and runs on top of Jupyter Notebook. It also features seamless integration with Google Drive. We use PyTorch, a flexible and powerful Python library for machine learning, to develop classifiers for the detection of cardiovascular diseases from input features that have been derived from the ECG and blood pressure signals. The models are built offline, on annotated datasets and once validated they are deployed on the cloud to carry out real-time inference for incoming patient data. A general flow comprises the pre-processing of raw ECG signals by employing Fourier Transform or wavelet analysis which gives features such as QRS complex width, RR intervals, and amplitude. These features are then passed into PyTorch models such as Decision Trees, Naive Bayes classifiers, or shallow neural networks to classify potential diagnoses such as arrhythmia, bradycardia, or hypertension. The analyses are presented on the Blynk interface using a REST API or Firebase, with the results coming back to the Arduino-interfaced application. This "connectivity module" methodology permits a system which can be evolved as new diagnostic models are designed. The software user interface for the proposed system is designed to be intuitive and easy to use so it can be easily used by a wide variety of users, which include medical professionals, caregivers, and elderly patients. It's mostly the Blynk App, as the UI. It includes a customizable dashboard with live data visualizations and health monitoring widgets. Users can read heart rate data by live number shows on the ECG device, by dynamic charts, and get alarms immediately via push notifications in case some abnormal ECG signals are found. Languageless color indicators effectively classify normal and critical physiological values and improve situational awareness among unproficient users. It also has a health summary logging feature, which enables to monitor the trend, patterns of daily/weekly/monthly health data, an important technical assistance to your long-term health condition track managing and health target setting. Furthermore, the system is flexible to be integrated in other IoT frameworks like thing Speak, Firebase, or node red to add advanced functionalities for research or clinical settings that demand more advanced data visualization and analysis. The

entire structure was thought in terms of efficient integration and real time data flow, starting from the data generated in the biomedical sensors inserted in the chest strap. Raw ECG and blood pressure signals are measured continuously through ECG electrodes and blood pressure sensors from the user. The analog signals are sent to the Arduino UNO, for the signal conditioning and the ADC. After digitalization, the data is transferred to a GSM based IoT module, which securely transmits it to cloud. Machine learning models trained on the sensor data are performed in the cloud, where platforms such as Google Colab run the trained models to identify possible anomalies or irregularities in the incoming accelerometer data. The diagnostic outcomes are transmitted to a cloud database over the Blynk mobile app, processed, secured, and results made available for real-time analysis. The app presents these insights in an easy-to-understand interface, allowing healthcare providers or caregivers to make well-informed decisions in a timely manner based on the insights generated. The end-to-end data pipeline enables accurate monitoring, rapid diagnostics and remote accessibility—critical for proactive care and as an early intervention in cardiovascular conditions.

## 2. CONCLUSIONS

The proposed Advanced Cardiac Health Monitoring System is a promising development towards the convergence of bio-sensing, Internet of Things, and machine learning for on-time cardiovascular-health-care. By incorporating ECG monitor, sphygmomanometer and blood temperature sensor into a wearable chest belt and allowing for continuous data analysis & cloud-based data service, the system provides a portable, non-invasive and cost effective solution for early prevention and continuous management of heart diseases. Machine learning algorithms enhance diagnostic accuracy, by categorizing heart rhythms and conditions and cloud connection makes retrieval accessible to caregiver and family. This work mitigates critical shortcomings of the current monitoring tools and lays the groundwork for smart, scalable, and patient-friendly healthcare technology, especially in the remote or resource-limited areas. Following additional clinical validation and enhancing the user interface, this system can revolutionize delivery of cardiac care and significantly shape the era of digital health.

## REFERENCES

- [1] Wan, Jie, Munassar AAH Al-awlaqi, MingSong Li,

- Michael O'Grady, Xiang Gu, Jin Wang, and Ning Cao, "Wearable IoT enabled real-time health monitoring system," *EURASIP Journal on Wireless Communications and Networking*, pp. 1-10, Dec. 2018.
- [2] Gomathy, C. K., and Mr A. Rohith Naidu, "The prediction of disease using machine learning," *International Journal of Scientific Research in Engineering and Management (IJSREM)*, pp. 1-7, Oct. 2021.
- [3] Yifeng Wang, Zheng Zhao and Jiangtao Li, "Current Status and Development Tendency of Wearable Cardiac Health Monitoring," *Chinese Journal of Electrical Engineering*, Vol.9, No.1, March 2023.
- [4] Mehri, Maroua, Guillaume Calmon, Freddy Odille, and Julien Oster, "A deep learning architecture using 3D vector cardiogram to detect R-peaks in ECG with enhanced precision," *Sensors* 23, Vol.2288, No. 4, Feb.2023.
- [5] Branislav Vajdic, "Accurate Reconstruction of the 12-Lead Electrocardiogram from a 3-Lead Electrocardiogram Measured by a Mobile Device," *IEEE Journal Research Article*, Vol.12, Jan 2024.
- [6] Hosam F. El-Sofany, "Predicting Heart Diseases Using Machine Learning and Different Data Classification Techniques," *IEEE Journal Research Article*, Vol.12, Aug 2024.
- [7] Priyanka Kakria, N. K. Tripathi, Peerapong Kitipawang, "A real-time health monitoring system for remote cardiac patients using smartphone and wearable sensors," *International journal of telemedicine and applications* 2015, Vol. 373474, No. 1, Dec 2015.
- [8] Manullang, Martin Clinton Tosima, Jonathan Simanjuntak, Ahmad Luky Ramdani, "Implementation of AD8232 ECG signal classification using peak detection method for determining point," *Indonesian Journal of Artificial Intelligence and Data Mining* 2, pp. 61-66, Sep 2019.
- [9] Aziz Saira, Sajid Ahmed, Mohamed-Slim Alouini, "ECG-based machine-learning algorithms for heartbeat classification," *Scientific reports* 11, pp.1, Vol.18738, Sep 2021.
- [10] Subba, Tanuja, Tejbanta Chingtham, "Comparative analysis of machine learning algorithms with advanced feature extraction for ECG signal classification," *IEEE Access*, April 2024.