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AI-Cardio: A Multi-Modal Explainable AI System for Heart Disease Detection, Prediction, and Personalized Healthcare Solutions

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Abstract: ***Cardiovasculardisordersremainamajorglobal health concern, often requiring continuous evaluation of cardiac activity for early detection and timely medical intervention. This researchpresentsanintelligentheartmonitoringsystemthat integratesInternetofThings(IoT)technologywithartificial intelligence to support real-time cardiac assessment. The system utilizes an ESP32 microcontroller as the central processing unit connectedtoanECGsensorforcapturingelectricalheartsignals and a DHT11 sensor to record body-proximal temperature and ambient humidity. The acquired data is wirelessly transmitted to a cloud platform for persistent storage and remote accessibility. Toenhancediagnosticcapability,thesystemincorporatesa machinelearningmodeltrainedtorecognizeirregularheart patternssuchasarrhythmia,tachycardia,andbradycardia. Additionally, an AI-poweredEC Ggraphinterpretationmodule enablesuserstouploadwaveformimagesandreceiveauto- matedanalyticalinsights, improvingusabilityforindividuals withoutmedicalexpertise.ThishybridintegrationofIoTsensing andAI-assistedanalyticscreatesa cost-effective,scalable,and continuouslyoperatingmonitoringsolutionsuitableforhome healthcare, telemedicineapplications, andlong-termcardiac observation.Theproposedsystemdemonstratesitspotentialto improvepersonalhealthtracking, reduceclinical dependency, andfacilitateearlyinterventionincriticalcardiacevents.***
Index Terms: component,formatting,style,styling,insert

I. INTRODUCTION

Cardiovascular diseases remain a major global health con- cern,oftenprogressingsilentlyuntilacriticalconditionarises, makingcontinuousandaccessiblecardiacmonitoringessential forearlyriskdetection.Conventionalmethodssuchasclinical ECG tests and Holter monitors are effective but limited to hospital environments, creating barriers for routine, long-term assessment, especially for elderly patients and individuals in remoteregions.LeveragingthegrowthofIoTandartificial intelligence, smart healthcare systems now enable real-time physiological monitoring, remote data access, and automated diagnostic support. The proposed Heart Monitoring System integrates an ESP32 microcontroller with an ECG sensor and DHT11 sensor to continuously record cardiac electrical sig- nals, temperature, and humidity while transmitting the data to acloudplatformforlong-termloggingandremotesupervision. Additionally, a machine learning model and AI-assisted ECG image interpretation provide intelligent abnormality detection and user-friendly insights, improving timely intervention and supporting preventive healthcare beyond traditional clinical settings.

A. Context and Motivation

Heart diseases often progress without early symptoms, requiringcontinuousmonitoringfortimelyintervention.Tradi- tionalhospital-basedECGsystemsarenotsuitableforroutine, long-term tracking, especially for elderly or rural patients. WithadvancementsinIoT,real-timesensingcanenableacces- siblecardiacassessmentoutsideclinicalenvironments.Cloud- baseddataloggingallows doctorstoremotely reviewhistorical vitals and detect risk patterns earlier. AI-assisted analysis supports automated interpretation, reducing dependency on specialized medical expertise

B. Objective

Themainobjectiveofthissystemistocontinuouslymonitor ECGsignalsalongwithtemperatureandhumidityinrealtime. Itaimstosecurely logallvitaldatatoacloudplatform for remote accessibility and long-term health tracking. The system integrates machine learning to identify abnormal car- diacpatternsautomatically.Additionally,AI-basedECGimage interpretation is included to support users who may not have medical expertise

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C. Significance
This system provides continuous and remote cardiac mon- itoring, reducing the need for frequent hospital visits. Cloud- based logging ensures that medical professionals can easily review long-term heart health trends. AI-driven ECG inter- pretation improves accessibility for users without clinical knowledge. Overall, the solution enhances early detection and preventive healthcare outcomes at an affordable cost

D. Background
Cardiovascular diseases require continuous monitoring be- cause several heart rhythm abnormalities appear sporadically and are not detected during short-duration clinical ECG tests [1],[8].TraditionalsystemssuchasHoltermonitorsarecostly and inconvenient for routine or long-term observation outside hospitals [4], [15]. IoT-enabled healthcare devices have there- fore gained attention for enabling real-time ECG acquisition and wireless remote monitoring using low-cost microcon- trollers like ESP32 [5], [6], [18], [20]. Compact ECG and environmental sensors such as AD8232 and DHT11 further improve measurement accuracy and physiological context [7], [17].Artificialintelligencetechniques,includingdeeplearning models, significantly enhance early diagnosis by accurately recognizing arrhythmias and waveform anomalies from ECG data [8], [14]. Cloud connectivity also enables secure storage of long-term vitals and supports telemedicine-based medical supervision [2], [16], [19].

II. SYSTEM ARCHITECTURE AND METHODOLOGY

A. System Overview
The system is designed as an IoT-enabled cardiac health monitoring solution that continuously tracks ECG signals along with temperature and humidity. The ESP32 microcon- troller handles sensor data and Wi-Fi transmission to thecloud for remote accessibility [5], [6], [18]. Machine learn-ing models are incorporated for ECG abnormality detection [8]–[14], while AI-assisted waveform interpretation supports users without medical expertise [11], [12]. This architecture ensures an affordable and scalable platform for preventive healthcare [2], [16].

B. Key Components
The ESP32 serves as the core processing unit due to itslow-power operation and integrated wireless connectivity [5], [6].TheAD8232ECGmodulecapturescardiacelectrical activityforreal-timemonitoring[7],[20].ADHT11sensor recordstemperatureand humidityvariationsthatinfluence physiologicalresponse[17].Acloudstorageplatformenables continuousdataaccess forcare giversand physicians[4],[19].

C. Data Storage and Integration
Real-time vital readings are transmitted through Wi-Fi to a secure cloud spreadsheet for continuous storage and remote monitoring [18], [19]. Timestamped logs support long-term cardiac trend analysis and pattern recognition [2], [16]. The stored data is also used for machine learning-based anomaly detection and AI-driven ECG image interpretation [8], [11].

D. Methodology
The ECG and environmental data are continuously col- lected, preprocessed, and wirelessly uploaded to the cloud using ESP32 [5], [6]. A trained ML model evaluates ECG patternstodetectarrhythmiasandirregularheartrhythms
[8]–[14]. Users can upload ECG images for AI-based wave- form evaluation, improving diagnostic assistive capabilities [11],[12].Thisend-to-endworkflowenhancesproactivemed- ical decision-making in cardiac health monitoring [1], [2].

III. SIGNAL PROCESSING AND HEARTRATE CALCULATION

Thecoreofthesystemistheacquisitionandanalysisof the Electrocardiogram (ECG) signal.

A. Digital Filterig (Preprocessing)
The ESP32 microcontroller performs basic digital filtering to remove noise (artifacts, baseline wander, and power line interference) from the raw ECG signal. The actual calculation forabasicdigitalfilter,likeanIIR(InfiniteImpulseResponse) orFIR(FiniteImpulseResponse)filter,involvesaconvolution oraweightedsumofinputand/orpreviousoutputsamples. A general equation for a digital filter output y[n] is:

$$y[n] = \sum_{k=0}^{M-1} b_k x[n-k] - \sum_{k=1}^{N} a_k y[n-k]$$

- Tx[n]isthecurrentinputsample(therawECGdata).
- y[n]isthecurrentoutputsample(thefilteredECGdata).
- x[n-k]andy[n-k]arepastinputandoutputsamples.
- $b_k$and $a_k$the filter coefficients (weights) that determine the filter's characteristics (e.g., whether it is a low-pass, high-pass, or band-pass filter).

B. HeartRate(HR)Calculation

Heart rate is calculated by determining the time interval between consecutive heartbeats, specifically the time between two consecutive R-waves (the tall peak of the QRS complex). ThistimeintervaliscalledtheR-Rinterval($T_R R$).

The formula for Heart Rate (HR) in Beats Per Minute (BPM) for a regular rhythm is:

$$\hat{H}R(\mathrm{BPM}) = \frac{60\text{seconds}}{T_{RR}(\text{seconds/beat})} \quad (1)$$

FordigitaldatasampledatafrequencyF_s(samples/second):

- Count the number of samples ($N_s amples$) between twoconsecutive R-peaks.
- Calculatethetimeinterval $T_R R$as:

$$T_{RR} = \frac{N_{\text{samples}}}{F_s} \quad (2)$$

- Substitute$T_R R$intotheHRformula

$$HR(\mathrm{BPM}) = \frac{60}{\frac{N_{\text{samples}}}{F_s}} = \frac{60 \times F_s}{N_{\text{samples}}} \quad (3)$$

C. MachineLearningAlgorithms

The ML model (CNN or LSTM) classifies the processed ECG signal for arrhythmias. These models work by calcu- lating feature maps and hidden states using complex matrix operations.

1) *ConvolutionalNeuralNetworks(CNNs):*ACNNuses a convolutional layer to extract features from the 1D ECG signal. This layer applies a filter (or kernel) over the inputdata.

The output of a 1D convolution O[i] at a position i is calculated by

$$O[i] = (I * K)[i] = \sum_k I[i+k] \cdot K[k] + b \quad (4)$$

- IistheinputECGsignalsegment.
- Kisthefilter/kernelweights.4
- bisthebiasterm.
- The filter weights (K) are what the model learns during trainingtodetectspecificpatterns(likeanabnormalQRS complex).

2) *Long Short-Term Memory (LSTM) Networks:* LSTMs are designed to handle sequential data (like ECG time-series) byselectivelyrememberingorforgettinginformationoverlong sequences using specialized structures called gates (Forget, Input, and Output gates).

The Forget Gate f_t(decides what to keep from the previous cell state $C_{t-1}$is a key calculation

$$\mathbf{f}_t=\sigma(\mathbf{W}_f\cdot[\mathbf{h}_{t-1},\mathbf{x}_t]+\mathbf{b}_f) \qquad (5)$$

- σisthesigmoidactivationfunction(outputsavalue between 0 and 1).
- $W_f$istheweightmatrixfortheforgetgate.
- $[\mathbf{h}_{t-1},\mathbf{x}_t]$aretheconcatenationofthepreviushidden state and the current input ECG sample.
- $b_f$isthebiasvector.

The final Cell State C_t(the "memory" of the network) is then updated using the forget gate:

$$\mathbf{C}_t=\mathbf{f}_t\odot\mathbf{C}_{t-1}+\mathbf{i}_t\odot\tilde{\mathbf{C}}_t \qquad (6)$$

- $\odot$ denoteselement-wisemultiplication.
- $i_t$istheInputGate(whatnewinformationtostore).
- $C_t$isthecandidatecellstate(newinformation).

The LSTM learns the weights (W) and biases (b) for all three gates to accurately classify the heart rhythm over time.

D. Advantages

The proposed system provides continuous real-time heart monitoring, enabling early detection of cardiac abnormalities thatmaybeoverlookedinbriefclinicaltests[1],[8].Its ESP32-based architecture ensures low cost and low power usage, making it ideal for home healthcare and deployment in ruralareaswithlimitedmedicalfacilities[5],[6],[18].Cloud data integration allows doctors and caregivers to remotely monitor long-term cardiac trends and ensure timely medical intervention [2], [16], [19]. Machine learning improves diag- nosticaccuracybyautomaticallydetectingECGirregularities reducing dependence on expert interpretation [8]–[14]. The AI-assistedECGimageanalysisfeatureenhancesusabilityfor non-medical users and supports telemedicine-based decision- making [11], [12]. Together, these capabilities provide an in- telligent, portable, and affordable cardiac monitoring solution for preventive healthcare.

IV. RESULT ANALYSIS

A. Performance Evaluation

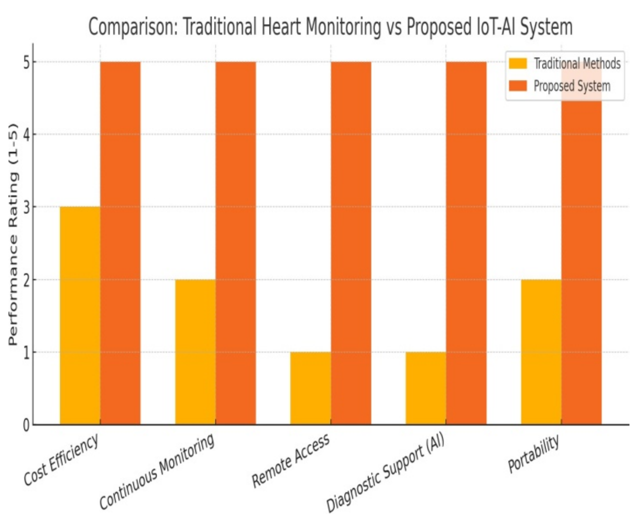

Fig.1.PerformancecomparisonbetweentraditionalECGmonitoringmethodsand the proposed IoT-AI heart monitoring system.

The performance comparison in Figure 01, traditional ECG systems provide clinically accurate cardiac readings but lack portability, continuous monitoring, and remote accessibility [1],[4],[15]. These limitations restrict early detection since di- agnosis depends on clinical presence and scheduled checkups [8]. The proposed IoT-AI system offers real-time data trans- missionandcloudintegration,enablingremoteandcontinuous cardiac supervision [2],[16],[19]. Machine learning and AI- based ECG analysis further support automatic abnormality detection without expert intervention [8],[14]. Overall, the system significantly enhances efficiency, accessibility, and response timing in cardiac healthcare [5],[6],[18].

Feature	TraditionalSystem	ProposedSmartSystem
CostEfficiency	Moderate	VeryHigh
ContinuousMonitor-ing	Limited(hospitalvisitre-quired)	24×7monitoring
RemoteAccess	Notsupported	Fullyremotecloudaccess
AI-BasedDiagnosticSupport	No	Yes
Portability	Low	HighlyPortable

TABLEI
COMPARISON BETWEEN TRADITIONAL AND PROPOSEDS MART SYSTEM

B. ComparativeAnalysis

It compares traditional cardiac monitoring approaches with the proposed IoT-AI system across major performance indi- cators. Although conventional ECG and Holter devices offer clinically reliable results, they are restricted to hospital envi- ronments and short-term usage, making continuous monitor- ing expensive and impractical for long-term supervision [1], [4], [15]. They also lack remote accessibility and automated diagnostic support, delaying early detection for patients expe- riencing periodic abnormalities [19]. In contrast, the proposed ESP32-based solution improves portability, cost efficiency, and home-care applicability [5], [6], [18]. With 24×7 monitoring, cloud integration enables remote supervision and long-term health analysis [2], [16], [19]. Additionally, machine learning and AI-driven ECG interpretation increase diagnostic confi- dence and provide users with immediate insights [8]–[14], [11],[12],makingthesystemamoreintelligentandpreventive healthcare technology.

Fig. 2.Real-time vital monitoring dashboard displaying heart rate, tempera-ture, humidity trends, and overall health status.

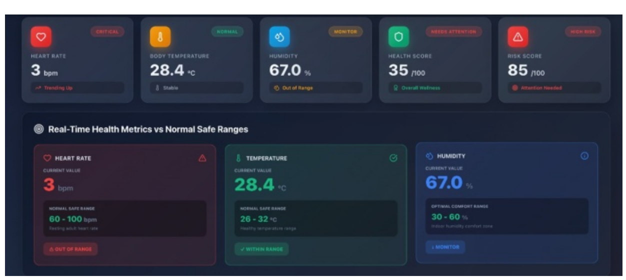

Fig.3.Visualizationofvitalsignassessmentwithsafetythresholdsandhealthscoring.

The functionality of the proposed IoT-AI cardiac monitor- ing system is demonstrated through its integrated interfaceand architecture. The system architecture (Figure 02) depicts the flow of ECG and vital data captured by sensors and transmitted via ESP32 to the cloud for continuous loggingandprocessing.

Fig. 4.AI-powered ECG analyzer interface supporting clinical-grade ECGupload and automated diagnostic analysis.

Thereal-timedashboarddisplaysmonitored parameters such as heart rate, temperature, humidity, health score, and alerts (Figure 03), allowing users and caregivers to instantlyassesscurrentphysiologicalconditionsanddetectab- normalities outside hospital settings. Further, the AI-powered ECG Analyzer interface adds diagnostic intelligence to the system(Figure04). Userscanupload ECGreportsindifferent formats, which are analyzed using machine learning-based ECG interpretation to identify potential cardiac irregularities. Together, these system components ensure seamless monitor- ing, remote accessibility, and advanced diagnostic support, offering a comprehensive and scalable solution for preventive cardiac healthcare.

V. USER FEEDBACK

Users responded positively to the system's real-time mon- itoring interface, stating that vital indicators were easy to understand. The color-coded alerts helped them quickly iden- tify abnormal conditions without medical knowledge. The AI- based ECG analysis feature was appreciated for providing quick interpretations of uploaded reports. Remote access to health data was seen as beneficial for elderly patients and caregivers. Participants felt the system could reduce unnec- essary hospital visits. Overall feedback indicated improved confidence in managing heart health at home.

Limitations and Challenges

Although the proposed IoT-AI heart monitoring system shows promising performance, some limitations still exist. Continuous Internet connectivity is required for real-time cloudmonitoring,whichmaynotbereliableinremoteregions. ECG signal quality can be affected by motion artifacts and incorrect electrode placement, impacting diagnostic accuracy. Thecurrentmodelsupportslimitedbiomedicalparametersand requires additional sensors for comprehensive cardiac assess- ment. AI interpretation depends on dataset diversity and may require clinical validation before real-world deployment.
Data privacyandregulatorycomplianceremainessentialchallenges for large-scale healthcare integration.

VI. FUTURE WORK

A. Implementation Considerations

Reliable network connectivity is necessary to ensure un- interrupted cloud data transmission and remote monitoring. Proper electrode placement and signal filtering techniques are required to maintain ECG accuracy during daily activities. Power-efficient operation of the ESP32 and sensors must be optimizedforextendedusageinportablesystems.Strong data protection measures, including encryption and secure communication, are essential to safeguard sensitive health in- formation.Additionally,compliancewithhealthcarestandards is needed for safe deployment in clinical and telemedicine environments.

B. Future Research Directions

Future work can focus on integrating additional biosensors such as SpO_2levels and blood pressure modules to expand clinicalmonitoringcapabilities.Advanceddeeplearningmod- els may be explored to improve diagnostic accuracy and support prediction of cardiac risks.

Wearable and battery- optimized hardware designs can enable fully mobile, contin- uous patient monitoring. Secure mobile app integration with alertnotificationscouldenhanceusabilityandreal-timehealth- care response. Further research on large-scale deploymentand hospital system interoperability will support adoption in telemedicine and smart healthcare ecosystems.

VII. CONCLUSION

The proposed IoT-AI heart monitoring system successfully demonstrates an efficient and accessible approach to continu- ous cardiovascular assessment. By integrating an ESP32 mi- crocontrollerwithECGandenvironmentalsensors,thesystem enables real-time vital data acquisition and cloud-based mon- itoring beyond hospital settings. The machine learning model and AI-powered ECG image analysis enhance diagnostic sup- port, allowing early detection of cardiac abnormalities evenforuserswithoutmedicalexpertise.Thesystemalsopromotes preventive healthcare through remote supervision and timely alerts, minimizing the dependency on frequent clinical visits. Overall, the solution proves to be cost-effective, scalable, and user-friendly, making it a suitable option for home healthcare, telemedicine, and long-term patient management. Future en- hancements such as additional biosensors, wearable design, and advanced analytics can further strengthen its clinical applicability and impact on smart healthcare ecosystems.

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