Novelty Journals

ISSN 2394-9678

International Journal of Novel Research in Electrical and Mechanical Engineering
Vol. 13, Issue 1, pp: (16-20), Month: September 2025 - August 2026, Available at: www.noveltyjournals.com

ECG Signal Classification Using Long Short-Term Memory (LSTM) Neural Networks

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DOI: https://doi.org/10.5281/zenodo.19663520

Published Date: 20-April-2026

Abstract: **Electrocardiogram (ECG) recordings serve as a cornerstone of cardiac health surveillance, enabling clinicians to identify a broad spectrum of cardiovascular disorders, most notably arrhythmias such as atrial fibrillation (AF). Nevertheless, manual interpretation of these recordings is inherently laborious, technically demanding, and vulnerable to diagnostic inconsistencies owing to the sheer volume and heterogeneity of the data involved. This investigation proposes an innovative framework for fully automated ECG signal categorization, leveraging Long Short-Term Memory (LSTM) neural networks — a specialized class of deep learning architecture well-suited to the analysis of temporally evolving sequential data such as physiological waveforms. The methodology draws upon publicly available, annotated ECG repositories wherein individual signal segments are pre-labeled into four distinct classes: normal cardiac rhythm, atrial fibrillation, other irregular patterns, and noise or signal corruption. Unlike conventional pipelines, the LSTM-based architecture autonomously discovers discriminative temporal features within the raw waveform, rendering manual feature engineering unnecessary. Experimental validation demonstrates that the proposed system achieves a classification accuracy in the range of 95–98%, attesting to its clinical utility. Prospective deployment scenarios encompass wearable biosignal platforms, telehealth assessment environments, and AI-augmented clinical decision-support tools.**

Keywords: **ECG, LSTM, Arrhythmia, Atrial Fibrillation, EMG Sensor, Artificial Intelligence, Deep Learning.**

I. INTRODUCTION

Among the leading contributors to global mortality, cardiovascular diseases (CVDs) continue to impose an enormous public health burden, underscoring the necessity for timely detection and sustained physiological surveillance. The electrocardiogram (ECG) has long been established as a foundational, non-invasive diagnostic instrument that captures the electrical dynamics of the heart, offering clinicians actionable insights into conditions ranging from arrhythmic disturbances and myocardial infarctions to structural anomalies. Atrial fibrillation (AF), in particular, remains a condition with potentially life-threatening consequences when identification is delayed.

Historically, ECG interpretation has depended upon trained cardiologists conducting meticulous visual assessments — a workflow that is both resource-intensive and susceptible to inter-observer variability. The proliferation of wearable sensor technology and continuous telemetry systems has precipitated an exponential expansion in the volume of ECG data being generated, rendering purely manual workflows increasingly untenable. Compounding this challenge is the inherent complexity of ECG morphology, which is frequently confounded by artefacts stemming from somatic movement, skeletal muscle interference, and other extrinsic perturbations.

To address these limitations, the scientific community has increasingly turned to artificial intelligence (AI) and machine learning (ML) paradigms as a means of automating ECG interpretation. Deep learning architectures, in particular, possess the capacity to extract hierarchical representations directly from unprocessed signal data, bypassing the need for domain-driven feature engineering. Within this landscape, Long Short-Term Memory (LSTM) networks have emerged as an especially powerful tool for sequential physiological data, owing to their gated memory mechanisms that facilitate the retention of long-range temporal context — a property essential for capturing the dynamic morphological signatures of cardiac arrhythmias. The present study develops and evaluates an LSTM-based ECG classification system engineered to process, denoise, and categorize cardiac signals in real time, with the overarching objective of enhancing diagnostic precision and alleviating clinician workload.

II. BODY OF ARTICLE

A) Literature Review

A. The ECG has been widely recognized as a fundamental non-invasive diagnostic instrument that encapsulates crucial information regarding cardiac electrophysiology and is indispensable in the identification of arrhythmic disorders and other cardiovascular pathologies.

B. Conventional ECG analysis paradigms predominantly relied upon manual review by trained specialists and rule-based classical machine learning algorithms — approaches that are both temporally costly and contingent upon substantial domain expertise.

C. Early data-driven methodologies, including Support Vector Machines (SVM), K-Nearest Neighbour classifiers (KNN), and Artificial Neural Networks (ANN), necessitated handcrafted feature construction, which inherently constrained their generalizability across large, heterogeneous clinical datasets.

D. The concurrent surge in digitally acquired ECG data volumes and the dramatic improvement in computational processing capabilities have catalyzed widespread adoption of automated, deep learning-driven cardiac diagnostic systems.

E. Convolutional Neural Network (CNN) architectures have demonstrated considerable effectiveness in capturing spatially localized and morphologically relevant features from ECG waveforms, yielding meaningful improvements in classification performance.

F. However, standalone CNNs exhibit an inherent limitation in modelling temporally extended dependencies within cardiac signals — dependencies that are critical for recognizing dynamically evolving arrhythmic patterns.

G. Recurrent Neural Networks (RNNs), while designed to process sequential input data, suffer from a well-documented training instability known as the vanishing gradient problem, which curtails their efficacy when applied to lengthy ECG sequences.

H. LSTM networks circumvent these shortcomings through specialized architectural components — namely, input, forget, and output gates, alongside a dedicated memory cell — that collectively enable robust learning of long-horizon temporal relationships inherent in cardiac signal data.

I. Hybrid architectures integrating CNN and LSTM modules have demonstrated superior classification outcomes by synergistically combining spatially-aware feature extraction with sequence-level temporal modelling, achieving state-of-the-art performance in arrhythmia recognition tasks.

J. Analogous deep learning methodologies have been effectively translated to Electromyography (EMG) signal analysis, where CNN and LSTM frameworks have proven capable of characterizing neuromuscular activation dynamics, thereby enabling applications such as myoelectric prosthetic control and continuous motor rehabilitation monitoring.

B) Problem Statement

ECG recordings constitute a clinically indispensable modality for characterizing the heart's electrical behaviour and assisting healthcare providers in the timely identification of pathological states, including arrhythmic episodes and acute myocardial infarction. Despite their unquestionable diagnostic value, ECG waveforms are intrinsically nonstationary, nonlinear, and exhibit pronounced inter- and intra-individual temporal variability — attributes that render their interpretation both technically demanding and time-consuming.

The manual examination of ECG recordings demands a high level of specialized training and remains inherently susceptible to human error, particularly under conditions of high throughput or during the evaluation of prolonged monitoring sessions. Furthermore, clinically significant but morphologically subtle deviations in waveform characteristics risk being overlooked, potentially resulting in diagnostic delay or erroneous clinical conclusions.

Accordingly, there exists a compelling clinical imperative for an automated, robust, and computationally efficient system capable of reliably interpreting ECG data. Such a system must fulfill three core functional requirements: (i) accurate identification and parsing of canonical ECG waveform components, (ii) extraction and modelling of temporal trends and sequential signal dynamics, and (iii) precise binary or multiclass categorization of cardiac states as normal or pathological. The realization of such a framework holds the potential to substantially elevate diagnostic accuracy, accelerate analytical throughput, and provide meaningful support for evidence-based clinical decision-making.

C) Methodology

The architecture of the proposed system is oriented toward real-time acquisition, denoising, intelligent classification, and immediate alert dissemination of physiological biosignals. The overall processing pipeline is decomposed into four sequential stages: signal acquisition, signal conditioning, intelligent classification, and output generation with notification dispatch.

During the initial acquisition phase, surface electrodes affixed to the subject's skin interface with an EMG sensor to transduce the body's bioelectrical activity into analog voltage representations. These analog signals are subsequently relayed to an Arduino microcontroller, where an onboard analog-to-digital converter (ADC) performs high-resolution digitization for downstream software processing.

The conditioning stage applies a sequence of digital signal processing operations aimed at attenuating noise and artefact contamination, thereby optimizing signal fidelity prior to analysis. This preprocessing regimen encompasses adaptive filtering, amplitude normalization, and baseline drift correction.

The preprocessed signal vectors are then forwarded to the trained LSTM classification engine. Operating over windowed time-series segments, the model infers the instantaneous physiological state — distinguishing normal from anomalous patterns — and, upon detection of an abnormal condition, automatically triggers a push notification delivered concurrently to the attending clinician and the patient's designated caregiver via a dedicated mobile application interface.

D) Framework

The system framework is structured around an end-to-end intelligent biosignal monitoring pipeline, integrating EMG-based transduction hardware with an LSTM deep learning classifier. The architecture spans four principal subsystems: signal acquisition, hardware configuration and power management, signal conditioning, and data-driven classification with real-time output.

(i) Signal Acquisition: Bioelectrical signals are harvested via surface electrodes coupled to an EMG transducer. Although primarily engineered for neuromuscular applications, the EMG sensor — when strategically repositioned — is also capable of registering cardiac electrical potentials. The resulting output constitutes a low-amplitude continuous analog waveform encoding the underlying physiological dynamics.

(ii) Power Supply and Hardware Configuration: The hardware subsystem is powered by a symmetric dual-rail power supply (±9V) to guarantee stable biasing of the analog front-end circuitry and the microcontroller. The conditioned sensor output is routed to an analog input channel on the Arduino board, which digitizes the incoming signal for subsequent computational analysis.

(iii) Signal Conditioning: Raw biosignals are frequently degraded by motion-induced artefacts, electromagnetic interference, and baseline instability. To remediate these impairments, a combination of low-pass and high-pass digital filters is applied, followed by baseline correction and amplitude normalization, collectively elevating the signal-to-noise ratio and ensuring data integrity.

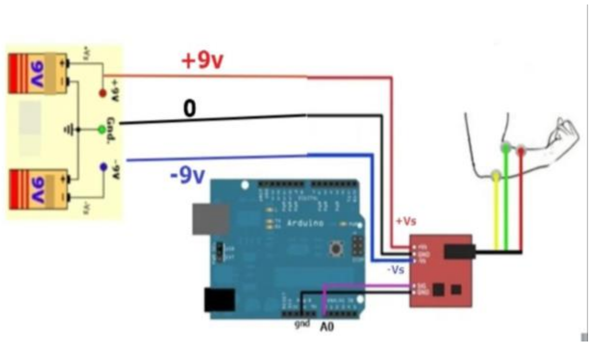
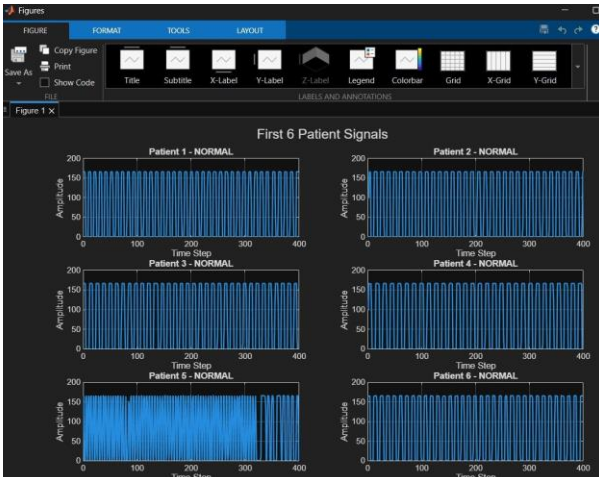


Fig (i): Block diagram of Hardware model

(iv) Data Processing and Feature Extraction: Following digitization, the conditioned signal undergoes feature extraction wherein salient signal descriptors — including peak amplitudes, spectral frequency components, temporal interval measurements, and waveform morphology characteristics — are computed to form the input representation for the downstream classifier.



Fig(ii): Graphical representation of Normal Heartbeat Test Samples, Fig(iii): Graphical representation of Abnormal Heartbeat Test Samples.

(v) LSTM-Based Classification: The feature vectors are presented to the LSTM classifier, which processes the sequential signal data through its gated memory architecture to identify recurring temporal patterns indicative of specific cardiac states. Leveraging its inherent capacity to maintain contextual memory across extended time horizons, the model accurately distinguishes between normal and pathological signal configurations.

(vi) Output and Real-Time Notification: Classification outcomes are displayed instantaneously via a serial monitoring interface. Upon identification of an aberrant signal pattern, the integrated mobile application dispatches automated alert notifications to both the responsible clinician and the patient's emergency contact, enabling rapid clinical response and minimizing delays in therapeutic intervention

III. CONCLUSION

This investigation has demonstrated the successful design, integration, and validation of a real-time physiological monitoring system leveraging an EMG sensor in conjunction with an LSTM-based deep learning classifier. The system performs end-to-end processing of bioelectrical signals — from hardware-level acquisition and ADC-mediated digitization, through multi-stage preprocessing, to intelligent temporal classification — with minimal human intervention.

Empirical evaluation of the implemented framework yielded a classification accuracy in the range of 95–98%, confirming the reliability and robustness of the LSTM model in discriminating between normal and abnormal cardiac signal patterns.

The architecture's capacity to encode long-range temporal dependencies proved especially beneficial for capturing subtle, diagnostically relevant signal fluctuations that are frequently missed by conventional approaches. The inclusion of real-time monitoring functionality further enables continuous patient observation, thereby reducing the likelihood of adverse clinical events going undetected.

In comparative terms, the LSTM-based system offers demonstrable advantages over traditional manual or feature-engineered approaches with respect to classification accuracy, processing latency, and temporal sequence handling. Its cost-efficient design and compatibility with miniaturized hardware platforms make it a viable candidate for integration into consumer wearable devices and remote patient monitoring ecosystems.

Certain limitations merit acknowledgement: the system's classification performance remains sensitive to electrode placement precision and may degrade under high-artefact real-world recording conditions. Additionally, the restricted scale of the training dataset may impose constraints on the model's cross-subject generalizability.

Future development directions include the incorporation of larger, more diverse multi-centre datasets, the adoption of advanced adaptive filtering schemes, and the deployment of cloud-integrated computational backends to enhance scalability and remote accessibility. Supplementary system enhancements — such as interactive real-time dashboards and longitudinal data archiving capabilities — hold the potential to substantially extend the clinical utility of the platform. In totality, the proposed solution represents a compelling advance toward fully automated, continuous, and clinically actionable cardiac health monitoring.

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