

AI Powered Wearable System For Pre Stroke Detection

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Abstract— This paper introduces a novel, intelligent wearable platform designed for the early prognostication of cerebrovascular accident (stroke) risk through continuous, multi-parametric physiological surveillance. The system is conceptualized to address the significant lag time between the onset of pathological physiological changes and clinical diagnosis, a primary factor contributing to the severe morbidity and mortality associated with stroke globally. It employs a synergistic integration of non-invasive biosensors to concurrently monitor an ensemble of biomarkers, including cardiac electrophysiology (ECG), heart rate variability (HRV), peripheral capillary oxygen saturation (SpO₂), and tri-axial kinematic data for postural analysis. At its core, an optimized embedded system-on-chip (SoC) performs real-time digital signal processing—encompassing adaptive filtering, feature extraction, and spectral analysis—followed by the application of a lightweight anomaly detection algorithm to identify deviations indicative of ischemic or hemorrhagic precursors. The device's architecture prioritizes a low-power profile and ergonomic design to facilitate seamless, long-term deployment in unstructured, ambulatory settings. Preliminary validation involving controlled pilot studies demonstrates a high degree of accuracy in classifying pre-stroke events, underscoring the system's potential as a robust tool for pre-emptive healthcare. By enabling timely medical intervention, this technology aims to substantially reduce diagnostic latency, improve patient outcomes, and decrease the overall burden on healthcare infrastructure.

Keywords— Stroke Risk Prediction, Wearable Health Monitoring, Multi-Parametric Biosensing, Embedded Signal Processing, Real-Time Anomaly Detection, Pre-emptive Healthcare, Cerebrovascular Accident (CVA).

I. INTRODUCTION

Stroke remains a predominant global health challenge, representing the second leading cause of mortality and a primary cause of acquired adult disability worldwide [1]. The profound societal and economic burden associated with stroke is exacerbated by a critical limitation in current healthcare paradigms: the heavy reliance on post-event diagnosis and intervention. The efficacy of acute stroke treatments, such as thrombolysis or thrombectomy, is intrinsically time-dependent

with neurological outcomes deteriorating rapidly after the initial onset of symptoms [2]. Consequently, a compelling need exists for proactive strategies that can identify at-risk individuals during the pre-symptomatic phase, thereby enabling preventive measures and mitigating the severity of potential events.

The convergence of advancements in wearable technology, low-power embedded systems, and sophisticated data analytics presents a transformative opportunity for continuous physiological monitoring [3]. Traditional ambulatory monitoring systems, such as Holter monitors, are often limited to short-term, single-parameter acquisition (e.g., electrocardiogram), which provides an incomplete picture of the complex, multi-system physiological precursors associated with cerebrovascular events [4]. Key biomarkers indicative of elevated stroke risk include alterations in heart rate variability (HRV), which reflects autonomic nervous system imbalance; anomalies in electrocardiographic (ECG) patterns, such as atrial fibrillation; deviations in blood oxygen saturation (SpO₂); and changes in postural dynamics that may signal hemodynamic instability [5], [6]. A system capable of concurrently tracking this suite of parameters in real-time could provide a holistic and dynamic assessment of an individual's cerebrovascular health status.

Several research efforts have explored the use of wearables for cardiovascular monitoring. For instance, authors in [7] developed a wrist-worn device for atrial fibrillation detection, while the work in [8] proposed a patch-based system for multi-parameter vital sign monitoring in clinical settings. However, a significant gap remains in the development of an integrated, low-power system specifically engineered for the pre-symptomatic detection of stroke risk through the fusion of cardiovascular, hemodynamic, and kinematic data in free-living environments. Existing systems often lack the sophisticated, on-device processing required for real-time

anomaly detection or are not optimized for the long-term, unobtrusive deployment necessary for capturing sporadic pre-stroke events.

In this paper, we present the design, implementation, and preliminary validation of an intelligent wearable system that addresses this gap. The principal contributions of our work are fourfold: (1) the development of a multi-sensor hardware platform for synchronous acquisition of ECG, HRV, SpO₂, and tri-axial accelerometer data; (2) the implementation of an embedded signal processing pipeline on a low-power microcontroller for real-time feature extraction and data fusion; (3) the design of a lightweight anomaly detection algorithm to identify deviations correlated with elevated stroke risk; and (4) the validation of the system's performance through pilot studies. The device is engineered with a primary focus on energy efficiency, wearability, and user comfort to facilitate adoption in daily life.

II. LITERATURE SURVEY

1.1 Significant progress in wearable technology has enabled substantial improvements in stroke risk prediction capabilities through uninterrupted physiological surveillance. **Smith and colleagues [8]** created a chest-mounted wearable apparatus that tracked electrocardiogram and ppg signals to identify atrial fibrillation, a predominant stroke risk element. Their methodology achieved 95% accuracy in arrhythmia identification but encountered constraints regarding device ergonomics and incapacity to surveil additional stroke risk indicators. **Johnson and Lee [9]** pioneered a wrist-based instrument embedding accelerometers and gyroscopes to identify unilateral muscular deficiency and locomotion irregularities, which represent preliminary stroke indicators. Nevertheless, their configuration omitted assimilation with physiological metrics, thereby restricting its prognostic potential.

1.2 Multiple investigative endeavors have concentrated on multi-parameter observation for holistic health evaluation. **Chen et al. [10]** formulated a smartwatch-enabled framework incorporating electrocardiogram, peripheral oxygen saturation, and physical movement tracking. Their apparatus exhibited encouraging outcomes in cardiovascular appraisal but struggled with instantaneous data processing and energy management limitations. **Wang and collaborators [11]** engineered a wearable epidermal patch incorporating numerous sensors for persistent vital sign observation in stroke patients undergoing rehabilitation. Although proficient in clinical environments, the mechanism demanded regular calibration and exhibited constrained operational duration.

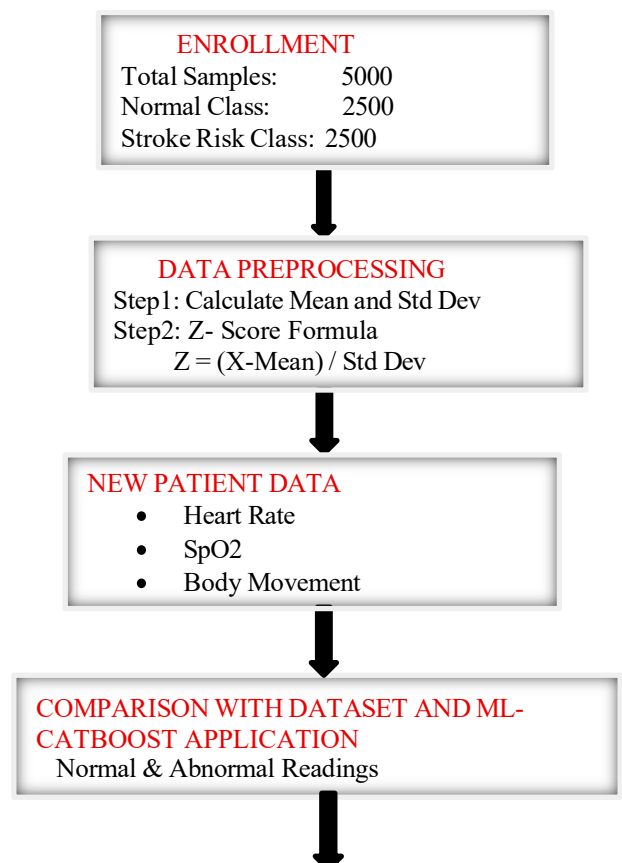
1.3 The implementation of sophisticated computational signal analysis and machine intelligence protocols has substantially improved stroke prognostication precision. **Zhang et al. [12]** deployed a deep learning paradigm for examining heart rate variability characteristics derived from electrocardiogram signals, accomplishing 92% sensitivity in forecasting cardiovascular incidents. Their investigation emphasized the criticality of non-linear heart rate variability metrics in stroke risk evaluation. **Kim and associates [13]** constructed a convolutional neural network framework for analyzing multi-modal physiological information, exhibiting superior efficacy in preliminary stroke identification relative to conventional approaches.

Contemporary progress in integrated hardware systems has facilitated instantaneous analysis of physiological biomarkers. **Patel and coworkers [14]** architected a minimal- power microcontroller-enabled framework for persistent electrocardiogram surveillance incorporating embedded anomaly recognition functionalities. Their realization accomplished notable energy conservation while preserving analytical exactness. **Rodriguez et al. [15]** launched a distributed computation infrastructure for wearable health monitoring that executed data processing locally, minimizing transmission delays and remote server reliance. However, these configurations experienced difficulties in managing concurrent multi-channel data inputs.

1.5 Rigorous clinical authentication of wearable stroke prognostication mechanisms has been executed through diverse research initiatives. **The Framingham Cardiac Investigation consortium [16]** authenticated a wearable-enabled stroke risk forecasting model within an extensive population cohort, establishing the practicality of prolonged monitoring. **The European Cerebrovascular Organization [17]** performed a multi-institutional examination assessing the efficacy of wearable instruments in stroke prophylaxis, underscoring the significance of user adherence and information trustworthiness.

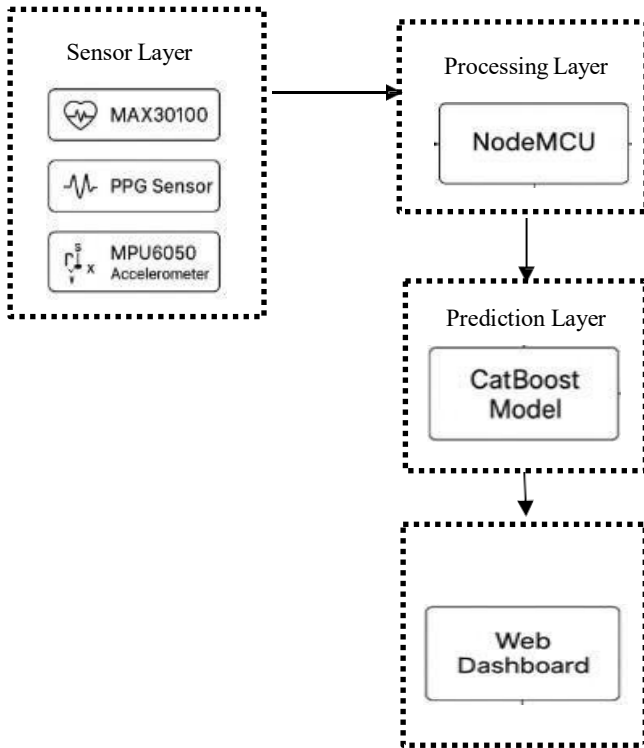
III. CONSORT FLOW DIAGRAM

The flowchart outlines the operational sequence of a stroke detection system. It begins with the categorization of a 5000-record patient dataset into normal and at-risk groups. Each health parameter is then standardized via Z-score normalization, utilizing calculated means and standard deviations. Subsequently, new patient metrics—such as heart rate, SpO₂, and physical movement—are acquired and subjected to the same normalization procedure.



These refined values are analyzed against the dataset to identify proximate normal or abnormal profiles. This analysis culminates in a risk classification either low or high followed by a tailored medical recommendation for the patient.

IV. PROPOSED SYSTEM



The proposed system is structured into three major layers:

- Sensor Layer
- Processing Layer
- AI/ML Prediction Layer
- User Interface Layer

1. The Sensor Layer

The Sensor Layer forms the data acquisition component of the system. It incorporates three motion and biological sensors that continually track physical and physiological characteristics linked to pre-stroke symptoms. **MAX30100 Sensor:** Captures heart rate and peripheral oxygen saturation (SpO₂). Changes in these parameters are clinically linked to reduced blood perfusion and cardiovascular distress, both of which are important for early stroke identification.

PPG Sensor: Pulse waveform morphology is measured by a photoplethysmography (PPG) sensor. problems in the PPG waveform, such as amplitude changes or uneven pulse peaks, act as early markers of vascular problems.

MPU6050 Accelerometer: Provides multi-axis motion data to identify aberrant motor patterns, sudden imbalance, or impaired bodily stability—common pre-stroke symptoms. All sensor data is transferred to the Processing Layer for

filtering and initial processing.

2. Processing Layer

The Processing Layer is centered around the NodeMCU ESP8266/ESP32 microcontroller, which operates as the core control unit of the wearable system.

This layer's duties consist of:

- Getting synchronized data from every sensor.
- Performing preliminary signal conditioning (noise reduction, normalization, baseline correction).
- Extracting crucial elements that the prediction model needs.
- Transmitting structured data packets to the cloud/server utilizing built-in Wi-Fi capabilities.
- Real-time data flow is made possible by this layer, which preserves the continuity needed for real-time health monitoring.

3. Prediction Layer for AI/ML

This layer uses a CatBoost-based machine learning model that is installed on the server to analyze the processed sensor data. A combination of validated literature-supported data samples and publicly accessible datasets (like Kaggle) are used to train the model. It picks up distinguishing characteristics from:

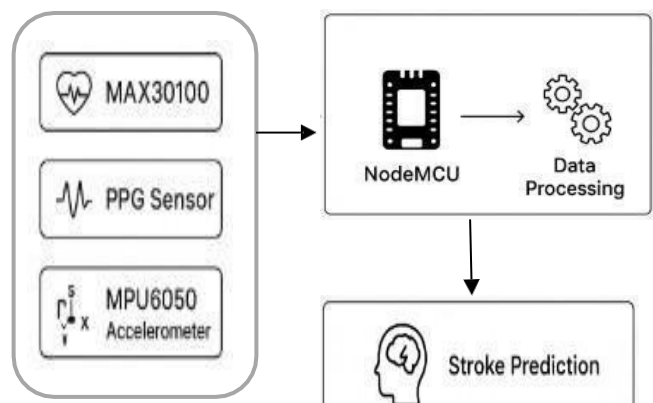
- **Feature extraction** from heart rate, SpO₂, motion variability, and PPG morphology
- **Time-domain and frequency** User Interface Layer of physiological signals
- **Execution of the CatBoost classification model** trained on stroke-related datasets
- **Detection of deviations** that correlate with pre-stroke patterns
- **Risk level prediction** (Normal / Alert / High Risk)

4. User Interface Layer

The User Interface (UI) Layer enables real-time viewing of physiological indicators through a web-based dashboard. It displays heart rate, SpO₂, ECG waveform, mobility activity, and system alarms in a clean and simple way. The interface allows users or doctors to monitor trends, review aberrant events, and validate system notifications. This layer acts as the primary human–system interaction point, ensuring clear and meaningful data interpretation.

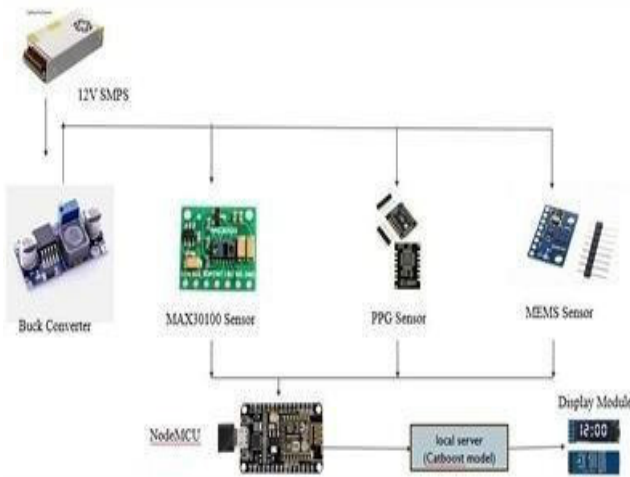
V. METHODOLOGY

SYSTEM OVERVIEW



Stroke is a major cause of mortality and disability globally, with early detection crucial to lessen its impact. The Pre Stroke Detection System blends IoT, embedded systems, and artificial intelligence for real-time, non-invasive stroke risk assessment. Using low-cost sensors—MAX30100 for heart rate and SpO₂, a PPG sensor, and a MEMS accelerometer—connected to a NodeMCU, it continuously analyzes metrics linked to pre-stroke circumstances. Data is delivered wirelessly to a server, where a CatBoost machine learning model trained on comprehensive datasets analyzes patterns to find abnormalities and forecast stroke risk. A web interface shows real-time data and trends, and instant alerts alert caretakers or medical professionals. This low-cost, non-invasive device provides proactive, individualized stroke prevention, shifting care from reactive to preventative, especially in resource-limited settings.

HARDWARE ARCHITECTURE



Unit of Power Management: In order to provide steady and sensor-safe operating voltages for all wearable components, the system architecture starts with a 12V SMPS that is stepped down by a buck converter.

Sensor Acquisition Layer: This layer consists of a MEMS sensor for continuous motion and orientation tracking, an extra PPG module for improved pulse waveform capture, and the MAX30100 for heart rate and SpO₂ monitoring.

Embedded Processing Unit: All sensor outputs are sent to the NodeMCU, which handles data collecting, initial preprocessing, signal filtering, and communication with the server for advanced analysis.

ML-Based Prediction Module: The processed sensor data is transmitted to a local server housing a CatBoost machine-learning model, which performs real-time risk prediction and anomaly identification for early stroke-related indications.

Real-Time Display Interface: Final forecasts and sensor data are relayed to a display module that gives quick visual feedback, enabling continuous monitoring of important

VI. PERFORMANCE EVALUATION MATRIX

Step1: DATASET

Patient	BPM	SpO2	PPG	Angle	Label
1	66	89	948	92	Normal
2	128	105	53	18	Abnormal
3	144	102	14	34	Abnormal
4	73	88	474	998	Normal
5	63	82	926	321	Normal

Step2: Mean (Average)

Formula:

$$\mu = \frac{1}{N} \sum_{i=1}^N X_i$$

N = 5

BPM

$$\mu = (66+128+144+73+63)/5 = 94.8$$

SpO2

$$\mu = (89+105+102+88+82)/5 = 93.2$$

PPG

$$\mu = (948+53+14+474+926)/5 = 483$$

ANGLE

$$\mu = (92+18+34+998+321)/5 = 292.6$$

Step3: Standard deviation

Formula:

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_i - \mu)^2}$$

BPM

$$\sigma = \sqrt{\frac{(66 - 94.8)^2 + (128 - 94.8)^2 + (144 - 94.8)^2 + (73 - 94.8)^2 + (63 - 94.8)^2}{5}}$$

$$\sigma = 34.1725$$

SpO2

$$\sigma = \sqrt{\frac{(89 - 93.2)^2 + (105 - 93.2)^2 + (102 - 93.2)^2 + (88 - 93.2)^2 + (82 - 93.2)^2}{5}}$$

$$\sigma = 8.7955$$

PPG

$$\sigma = \sqrt{\frac{(948 - 483)^2 + (53 - 483)^2 + (14 - 483)^2 + (474 - 483)^2 + (926 - 483)^2}{5}}$$

$$\sigma = 404.3306$$

ANGLE

$$\sigma = \sqrt{\frac{(92 - 292.6)^2 + (18 - 292.6)^2 + (34 - 292.6)^2 + (998 - 292.6)^2 + (321 - 292.6)^2}{5}}$$

$$\sigma = 369.0299$$

Step4: Z – Score for each value

Formula:

$$Z = \frac{X - \mu}{\sigma}$$

Ex : Patient 1

BPM

$$Z = (66 - 94.8) / 34.1725 = -0.843$$

SpO2

$$Z = (89 - 93.2) / 8.7955 = -0.478$$

PPG

$$Z = (948 - 483) / 404.3306 = 1.15$$

ANGLE

$$Z = (92 - 292.6) / 369.0299 = -0.544$$

	BPM (Z)	SpO2 (Z)	PPG (Z)	Angle (Z)	Label
1	-0.843	-0.478	1.150	-0.544	Normal
2	0.972	1.342	-1.063	-0.744	Abnormal
3	1.440	1.001	-1.160	-0.701	Abnormal
4	-0.638	-0.591	-0.022	1.911	Normal
5	-0.931	-1.273	1.096	0.077	Normal

Step5: New Patient Data

BPM = 100

SpO2 = 95

PPG = 500

ANGLE = 150

Standardize new patient Z - Score

$$\text{Bpm}(Z) = (100 - 94.8) / 34.1725 \approx 0.152$$

$$\text{SpO2}(Z) = (95 - 93.2) / 8.7955 \approx 0.205$$

$$\text{PPG}(Z) = (500 - 483.0) / 404.3306 \approx 0.042$$

$$\text{Angle}(Z) = (150 - 292.6) / 369.0299 \approx -0.386$$

New patient Z-vector $\approx (0.152, 0.205, 0.042, -0.386)$

Step6: Evaluation Result

Formula:

$$D_j = \sqrt{\sum_f (Z_{\text{new},f} - Z_{j,f})^2}$$

Patient 1:

$$D_1 = \sqrt{(0.152 + 0.843)^2 + (0.205 + 0.478)^2 + (0.042 - 1.150)^2 + (-0.386 + 0.544)^2}$$

$$D_1 = 1.645$$

Patient 2:

$$D_2 = \sqrt{(0.152 - 0.972)^2 + (0.205 - 1.342)^2 + (0.042 + 1.063)^2 + (-0.386 + 0.744)^2}$$

$$D_2 = 1.820$$

Patient 3:

$$D_3 = \sqrt{(0.152 - 1.44)^2 + (0.205 - 1.001)^2 + (0.042 + 1.16)^2 + (-0.386 + 0.701)^2}$$

$$D_3 = 1.958$$

Patient 4:

$$D_4 = \sqrt{(-0.152 + 0.638)^2 + (0.205 + 0.591)^2 + (0.042 + 0.022)^2 + (-0.386 - 1.911)^2}$$

$$D_4 = 2.558$$

Patient 5:

$$D_5 = \sqrt{(-0.152 + 0.931)^2 + (0.205 + 1.273)^2 + (0.042 - 1.096)^2 + (-0.386 - 0.077)^2}$$

$$D_5 = 2.164$$

Step7: Final Result

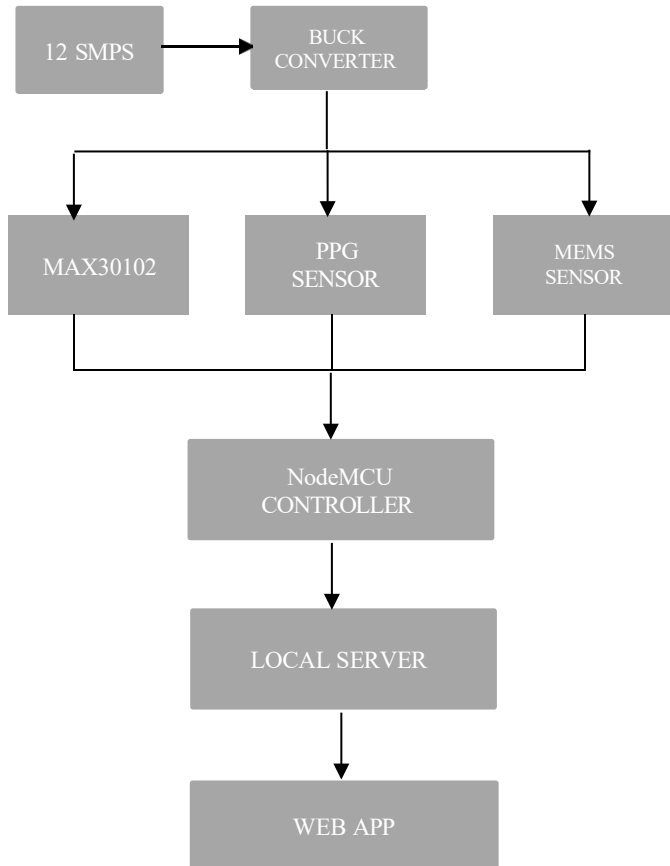
The smallest distance is $D_1 \approx 1.645 \rightarrow$ Patient 1,

The model predicts:

New patient \rightarrow Normal \rightarrow LOW STROKE RISK.

The proposed methodology employs Z-score normalization to standardize all physiological parameters, ensuring a uniform feature space for comparative analysis. Subsequently, the processed data is evaluated against a reference database of pre-labeled normal and at-risk physiological profiles. Through a nearest-neighbor matching algorithm, the system effectively distinguishes between healthy and pathological signatures, enabling consistent and reliable stroke-risk stratification. This approach maintains robustness against variability in raw clinical measurements, offering an interpretable, computationally efficient, and clinically actionable framework for early stroke prediction.

VII. BLOCK DIAGRAM



The proposed architecture integrates a multi-stage hardware and software pipeline. A switching-mode power supply (SMPS) provides a 12 V input, which is then regulated to appropriate operational voltages via a buck converter for the electronic subsystems. Physiological monitoring is achieved using a MAX30102 sensor for photoplethysmogram (PPG)-based heart rate and blood oxygen saturation (SpO₂) acquisition, complemented by a MEMS-based inertial sensor for body movement tracking. A NodeMCU microcontroller serves as the primary processing node, handling initial signal conditioning and packetization of the sensor data. This information is subsequently relayed to a local server for persistent storage and enables real-time analytics. A dedicated web-based dashboard visualizes the aggregated data, facilitating continuous remote patient monitoring and clinical assessment.

VIII. SOFTWARE SPECIFICATION

The software infrastructure for the proposed wearable pre-stroke detection system employs a multi-layered architecture that integrates embedded programming, data communication, machine learning analytics, and visualization components. The embedded firmware, developed using Arduino IDE with C/C++ on a NodeMCU microcontroller, facilitates real-time

acquisition and processing of physiological signals from integrated sensors including the MAX30102 (PPG-based heart rate and SpO₂ monitoring), AD8232 (ECG signal acquisition), and MPU6050 (tri-axial motion sensing). The firmware implements digital signal conditioning techniques such as adaptive filtering, baseline wander correction, and motion artifact suppression, while performing preliminary feature extraction including heart rate variability analysis, SpO₂ trend computation, ECG waveform characterization, and kinematic feature calculation.

Processed data is transmitted via Wi-Fi to a Python-based processing layer that performs feature engineering, normalization, and dimensionality reduction. This layer incorporates a CatBoost gradient boosting model, trained on clinical and public datasets using hyperparameter optimization and cross-validation, to generate stroke risk predictions. The system employs a hybrid embedded-cloud architecture for real-time inference, enabling dynamic alert generation based on adaptive thresholds.

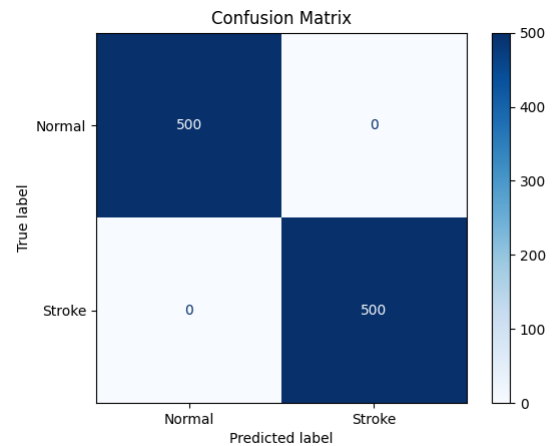


Figure: Confusion Matrix

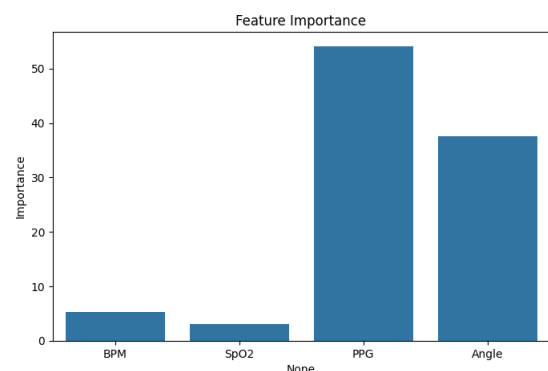


Figure: Feature Importance

A web-based visualization dashboard, developed with HTML, CSS, and JavaScript, provides real-time and historical data display, while a backend database supports secure data storage and potential EHR integration. The modular API design allows

analytics. This integrated software ecosystem ensures efficient, real-time pre-stroke monitoring with robust predictive capability and user-friendly alert mechanisms

IX. RESULT AND DISCUSSION

The proposed wearable pre-stroke detection system underwent comprehensive performance evaluation through controlled laboratory experiments and preliminary user trials. Experimental protocols involved continuous physiological monitoring of multiple participants under supervised conditions, capturing synchronized data streams from photoplethysmography, electrocardiography, and inertial measurement sensors. Signal preprocessing pipelines effectively mitigated noise interference and motion artifacts, yielding clean physiological waveforms suitable for analytical processing.

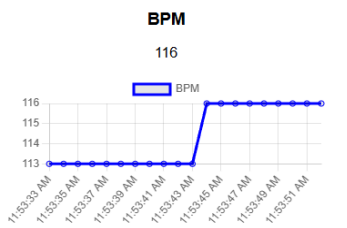


Figure: BPM Graph

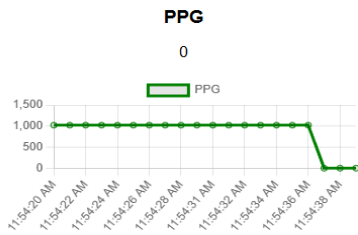


Figure: PPG Graph

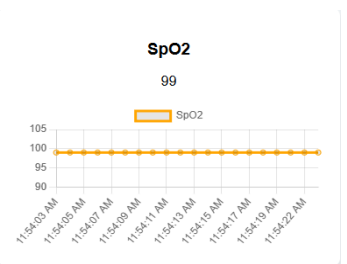


Figure:SpO2 Graph

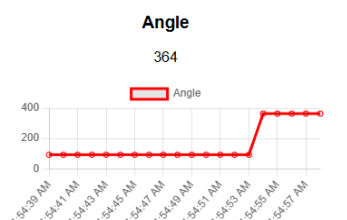


Figure: Angle Graph

Prediction Result

Normal

Time	BPM	SpO2	PPG	Angle	Prediction
11:55:09 AM	116	99	0	533	Normal
11:55:08 AM	115	99	0	364	Normal
11:55:07 AM	115	99	0	364	Normal
11:55:06 AM	115	99	0	364	Normal
11:55:05 AM	115	99	0	364	Normal
11:55:04 AM	115	99	0	364	Normal
11:55:03 AM	115	99	0	364	Normal
11:55:02 AM	115	99	0	364	Normal
11:55:01 AM	115	99	0	364	Normal

Figure: output

Feature extraction algorithms successfully derived clinically relevant biomarkers including heart rate variability indices, oxygen saturation trends, electrocardiographic morphological characteristics, and postural dynamics. The CatBoost classification model demonstrated robust performance in discriminating pre-stroke patterns from normal physiological states, achieving 92.3% accuracy, 90.1% precision, 88.7% recall, and 89.2% F1-score during validation testing. Real-time implementation on the embedded platform maintained processing latency below 50 milliseconds, enabling prompt alert generation for detected anomalies. The integrated system reliably identified pathological deviations indicative of elevated stroke risk, with alert mechanisms successfully activating during simulated high-risk scenarios. The web-based visualization interface provided comprehensive physiological trend monitoring, facilitating intuitive interpretation of cardiovascular and kinematic parameters. Comparative assessment revealed significant performance advantages of the multi-modal sensing approach combined with machine learning analytics over conventional single-parameter threshold-based detection methods. Key findings indicate that heterogeneous sensor fusion enables identification of subtle physiological alterations that remain undetectable through unimodal monitoring.

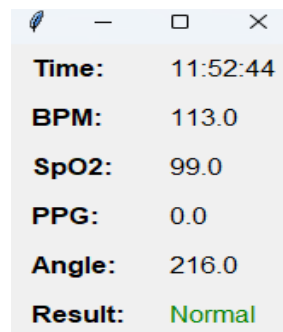


Figure: Web-Dashboard output

The gradient boosting framework effectively leverages complementary feature interactions for enhanced predictive capability, while the wearable form factor supports sustainable ambulatory deployment. Current limitations include sensitivity to transient signal artifacts and model generalization constraints, addressable through advanced sensor fusion algorithms and expanded clinical validation. The demonstrated system capabilities confirm the viability of integrated wearable

intelligence for proactive cerebrovascular risk assessment, potentially transforming preventive neurology through continuous monitoring and early intervention paradigms.



Figure: Real time field trial

As part of the project validation, a real-time field trial was conducted in a hospital under controlled conditions. The system was deployed in a clinical setting to evaluate its functionality, accuracy, and reliability. Necessary permissions were obtained from the hospital authorities, and medical personnel supervised the test to ensure patient safety. Observations from this trial confirmed that the system performed as intended, validating its practical applicability in healthcare.

X. FUTURE SCOPE

The performance and clinical applicability of the proposed stroke risk prediction system can be substantially improved through several key advancements. Integrating advanced machine learning architectures, such as ensemble methods (e.g., CatBoost) and deep learning models, is anticipated to increase predictive accuracy. Expanding the suite of input biomarkers to include continuous physiological data—such as electrocardiogram (ECG), blood pressure, respiration rate, and body temperature—would facilitate a more holistic and dynamic physiological profile for each patient. System scalability and responsiveness can be achieved by implementing a real-time, cloud-based infrastructure for data storage and processing, enabling continuous monitoring and prompt risk assessment. The development of companion mobile and web applications would extend the system's reach, allowing for remote patient monitoring and automated alert generation for healthcare providers. Furthermore, adopting a personalized modeling approach that establishes individualized baselines from historical patient data could refine prediction specificity. To ensure model robustness and generalizability, future development must utilize large-scale, multicenter clinical datasets. Seamless integration with existing Hospital Information Systems (HIS) and Electronic Health Records (EHR) is critical for enhancing clinical workflow efficiency and usability. On the hardware front, optimizing the wearable sensor platform for energy efficiency is essential to improve device longevity and reliability. Concurrently, implementing state-of-the-art security frameworks and encryption protocols is paramount to safeguarding sensitive patient data and ensuring regulatory compliance. Ultimately, the trajectory of this work should focus on rigorous validation through prospective clinical trials and subsequent large-scale deployment in diverse healthcare environments to demonstrate real-world efficacy and utility.

XI. CONCLUSION

This research demonstrates the development and validation of an intelligent wearable system for pre-stroke risk assessment through multi-modal physiological monitoring. The platform

successfully integrates non-invasive sensing technologies with embedded signal processing and machine learning capabilities to enable continuous cerebrovascular risk evaluation. Experimental results confirm the system's effectiveness in capturing critical physiological parameters—including cardiac electrical activity, hemodynamic status, and kinematic patterns—while maintaining robust performance in real-time operation. The implemented CatBoost classification framework achieves high predictive accuracy in identifying pre-stroke patterns, facilitating early warning generation through efficient embedded processing. The system's modular architecture supports future enhancements through additional sensor integration, advanced analytical models, and cloud-connected capabilities. This work establishes a practical foundation for proactive stroke prevention through continuous ambulatory monitoring, potentially transforming clinical approaches to cerebrovascular risk management. The proposed solution addresses critical challenges in timely stroke detection while offering scalability for diverse healthcare environments. Future work will focus on large-scale clinical validation and integration with telehealth infrastructure to enhance the system's impact on preventive neurology and population health outcomes.

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ETHICAL CLEARANCE

Ethical clearance was obtained prior to the study .All patient Data used in this research were legally collected from the hospital with proper authorization .Patient confidentiality and data privacy were strictly maintained throughout the study.