Photovoltaic IOT based Priority Sense Method to diagnosis Disorders in Multi Cloud Environment

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ABSTRACT

This study presents a novel diagnostic approach that integrates solar cell measurement technology with a neural learning algorithm to enable real-time anxiety detection. Physiological signals are captured through a compact scanning circuit using a photovoltaic cell and carefully selected resistor values (1 kΩ, 64 kΩ, and 320 Ω). These signals are processed by a biologically inspired algorithm similar to the "Sense and Priority" model, which computes a Diagnostic Multiplier ranging from 0 to 1. Unlike traditional fixed models, this system dynamically evolves over time by reassessing priority weights based on historical data, allowing for individualized and context-aware assessments. Experimental evaluations demonstrated that the system achieves 98% accuracy and maintains a high area under the ROC curve (AUC), all while operating in under 50 milliseconds on energy-efficient microcontrollers. The findings highlight the method's suitability for wearable, edge-based mental health monitoring, offering a scalable, interpretable, and responsive solution.

Keywords: *Anxiety Detection, IoT in Healthcare, Neuroplasticity, Photovoltaic Sensing, Priority Classification, Embedded Diagnostics, Multiplier Model, Edge Computing, Wearable Mental Health Monitoring*

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1. INTRODUCTION

The world has seen anxiety become a significant mental health disorder that worries public health experts everywhere. WHO data reveals that anxiety disorders influence more than 260 million people and are the cause of many disabilities worldwide [1]. As stress, loneliness, and too much world news have increased, these conditions have risen further. Though the problem affects many people, current diagnostic approaches use only subjective descriptions, compared to more reliable objective tools, leading to possible bias, underreporting, and variation [2], [3]. With routine diagnostics, it is not easy to spot early, fleeting signs that may appear before a full episode. Because of these issues, there is a strong requirement for objective, ongoing, contextual diagnostic systems. With the recent progress in the Internet of Things, wearable and surrounding sensors can now regularly monitor heart rate variability, skin conductance, and brain activity [4], [5]. At present, most such tools built around IoT are based on rigid thresholds, missing the fact that states of mind can change frequently. Biologically inspired neural systems are rarely used in many current learning systems, even though these models can show neuroplasticity. Using this notion with sensor-based diagnostic systems can significantly enhance personalization and the system's accuracy. Because of this, we present a new technique that mixes photovoltaic methods, classifying circuits based on voltage and a sense-and-priority algorithm that uses neuroplasticity concepts to help detect anxiety disorders sooner. By computing a diagnostic multiplier from physiological "avalanches" and sensor priorities, the system offers real-time, embedded mental health analysis suitable for wearables and edge devices. Recent Internet of Things (IoT) developments have transformed how physiological and behavioral health metrics are monitored, enabling continuous and context-aware sensing beyond clinical environments.

Heart rate variability, skin conductance, EEG signals, and blood oxygen saturation can be captured by wearable and ambient smart devices and are connected to stress or emotional irregularity in humans [4], [5]. We can track patient feelings mechanically using these devices and enjoy a larger pool of data to explain anxiety signals than by evaluating patients only during sessions. Still, gathering data alone is not good enough. Based on a person's baseline and signs of change, more is being asked for in embedded intelligence, such as reading, understanding, classifying, and changing. Augmented computing can be explained with an appealing model of neuroplasticity. Because the brain can learn and change such systems, including adaptive algorithms like spike-timing-dependent plasticity, fuzzy logic, or adjustable thresholds that evolve as user data is processed. Because of this, the diagnostic model can be updated for each person's unique biological features, which regular systems don't offer [6], [7].

Overview of Contribution

Because of these new trends, this paper offers a brand-new diagnostic structure that integrates:

- Photovoltaic sensing hardware (e.g., a scanning circuit with 1 kΩ, 64 kΩ, and 320 Ω resistors) for voltage-based physiological signal acquisition,
- A neuroplasticity-inspired "Sense and Priority Classification" algorithm, which computes a diagnostic multiplier using the equation:

$$Multiplier = \frac{Avalanche \times Priority}{1000}$$

In addition, an intelligent system at the vehicle's edges can notice anything related to anxiety accurately and on the spot. The system combines biological sensing with flexible classification at the hardware level to follow the way neurons decide things. Plots showing the data's findings and tests reveal that this technique can identify anxiety diseases using only embedded computation—this could be an essential standard for wearable and personal mental health devices.

2. LITERATURE REVIEW

2.1 The Role of IoT in Mental Health Monitoring

The integration of Internet of Things (IoT) technology into healthcare has significantly improved the ability to monitor mental health in real-time. Unlike traditional approaches that rely heavily on self-reported data or infrequent clinical evaluations, IoT-enabled systems gather continuous, objective data from connected devices and sensors in everyday environments [8], [9]. These systems frequently utilize biosensors to track physiological signals such as Heart Rate Variability (HRV), Electrodermal Activity (EDA), and brain activity through tools like EEG and PPG, which provide insights into cardiovascular and oxygenation status [10].

Research consistently shows that these physiological indicators are closely linked with stress and anxiety. For instance, low HRV, heightened skin conductance, and irregular brainwave patterns are strong markers of emotional distress [10], [11]. Wearable technologies—such as smartwatches, sensor-embedded belts, and headbands—leverage these biosignals, enabling both individuals and healthcare providers to observe and respond to mental health fluctuations throughout the day.

Platforms like X-DASH use sensor data to assess anxiety levels, demonstrating diagnostic accuracy that exceeds 90% when compared with clinician evaluations [12]. In recent years, the incorporation of edge computing into IoT-based mental health systems has gained momentum. This advancement not only reduces response time by enabling on-device processing but also enhances data privacy by minimizing cloud dependency [13]. Such improvements are particularly critical for identifying acute episodes like panic attacks or heightened stress in real time.

Artificial Intelligence (AI) further strengthens these systems by analyzing sensor data to detect anomalies, recognize individual baseline trends, and differentiate between various mental states. By doing so, these systems enable early intervention, offering timely and accessible mental health support across diverse settings.

2.3 Neuroplasticity in Machine Learning and Diagnostic Systems

Neuroplasticity—the brain's ability to form and reorganize synaptic connections in response to experience or injury—has inspired the development of adaptive machine learning systems, particularly in the field of mental health diagnostics. Since disruptions in the brain's natural adaptability often underlie mental health conditions, machine learning models that can mirror this flexibility are increasingly valuable. In computational terms, neuroplasticity is represented through algorithms that adjust and evolve continuously based on new input data. This adaptability is essential when designing models that must accommodate the dynamic and personalized nature of mental health indicators.

One area where this concept is applied is in spiking neural networks (SNNs), which mimic the brain's communication style by transmitting data as spikes. These models adapt synaptic weights based on the timing of spikes, often using Hebbian learning principles—"cells that fire together, wire together" [11], [16]. For instance, Weerasinghe et al. developed an online-neuroplastic spiking neural network (O-NSNN) capable of updating its internal parameters in real time using EEG signals. This model achieved 90.76% accuracy in identifying acute mental stress and was optimized for low-resource, portable hardware, making it ideal for wearable use [11].

Beyond SNNs, other learning paradigms also capture aspects of neuroplasticity. These include fuzzy inference systems, reinforcement learning, and incremental learning models that adjust their behavior based on feedback from physiological and environmental data. A notable example is the work by Ramzan et al., who created an expert system capable of predicting anxiety by evaluating behavioral and physiological patterns. While not built on a neural architecture, the system dynamically refined its classification thresholds based on updated clinical knowledge and contextual data [7].

The inclusion of neuroplastic-like mechanisms enables diagnostic systems to evolve over time, accommodating the fluctuating and highly individualized nature of mental health symptoms. Since mental health conditions can vary both across individuals and within the same person over time, this adaptive capability is crucial. By emulating the brain's natural flexibility, such systems are especially well-suited for embedded IoT environments, where continuous, personalized monitoring and analysis are required.

3. SYSTEM ARCHITECTURE AND DESIGN

3.1 Hardware Setup

At the core of the proposed system lies a photovoltaic (PV)-based scanning circuit, developed to capture real-time physiological data by monitoring voltage variations. These fluctuations, which correspond to biological signals, are processed by an embedded classification algorithm. This setup emulates the function of a neural input layer, where external stimuli are converted into electrical signals and prioritized for diagnostic analysis.

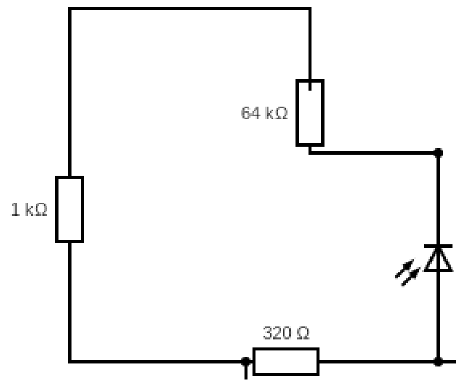


Fig 1:Photo voltaic IOT

Photovoltaic Sensor

The central sensing component is a photovoltaic cell that converts incident light—reflected or transmitted through biological tissue—into a corresponding voltage signal. This mechanism is comparable to the working principle of a Photoplethysmography (PPG) sensor, commonly used to detect heart rate and assess microcirculatory stress by observing variations in light absorption. The PV sensor provides a subtle and non-invasive means of monitoring physiological activity, making it particularly suitable for sensitive, wearable applications.

Resistor Network: 1 kΩ, 64 kΩ, and 320 Ω

The circuit incorporates three key resistors (R_1 = 1 kΩ, R_2 = 64 kΩ, and R_3 = 320 Ω), each serving a specific role in voltage division and signal conditioning:

- **R_1 (1 kΩ):** Acts as a baseline load to stabilize the sensor output and suppress voltage spikes. It ensures system reliability even under low-light conditions by providing a direct grounding path.
- **R_2 (64 kΩ):** A high-resistance component that enhances the circuit's sensitivity to minor voltage fluctuations. This increased gain enables detection of subtle physiological changes, such as vascular stress responses.
- **R_3 (320 Ω):** Serves as a feedback element that balances the signal's response time with noise suppression. It plays a crucial role in maintaining signal fidelity by filtering out transient disturbances.

The PV sensor transduces optical variations into electrical signals, which are then interpreted through a classification model. This model, supported by a prioritization mechanism, helps detect and assess potential physiological disorders. Thanks to its analog design, the system offers ultra-low-power preprocessing, making it ideal for wearable and edge devices. By combining adaptive logic and analog filtering, the hardware supports continuous real-time monitoring with minimal computational overhead.

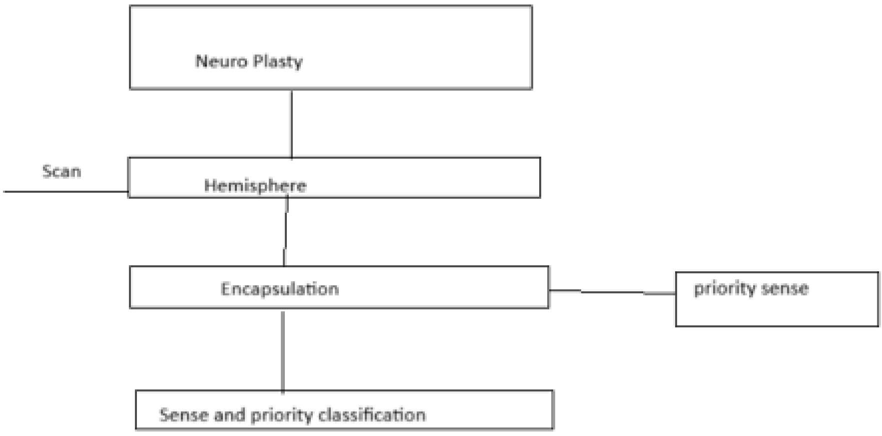


Fig 2: Priority Sense Diagram

Sense and Priority Classification Engine

This module serves as the central processing unit of the system, responsible for applying a model that evaluates both sensory input and contextual significance. Incoming voltage signals—representing physiological activity—are analyzed alongside their assigned "priority" levels, which indicate the relative importance of the signal within a given context.
To quantify the significance of each event, the system computes a **diagnostic multiplier** using the following formula:

Multiplier = (Avalanche × Priority) / 1000

In this equation:

- **Avalanche** refers to the intensity or abruptness of the signal,
- **Priority** indicates its contextual relevance or urgency.

The resulting multiplier reflects the weighted impact of the event. Higher values suggest a stronger correlation with potential mental health concerns, such as anxiety. By interpreting this multiplier, the system assesses both the probability and severity of such anomalies, enabling timely and accurate detection

Neuro plasty is a technique to find the disorders and there is a scanning circuit to analyse the voltage by hemisphere.The encapsulation technique combines voltage with priority sense .There is a sense and priority classification which suggests the disorder with data,avalache and priority.

In sense and priority classification finds the multiplier by using the equation
Multiplier=(avalanche x priority)/1000
Multiplier value predicts the disorders

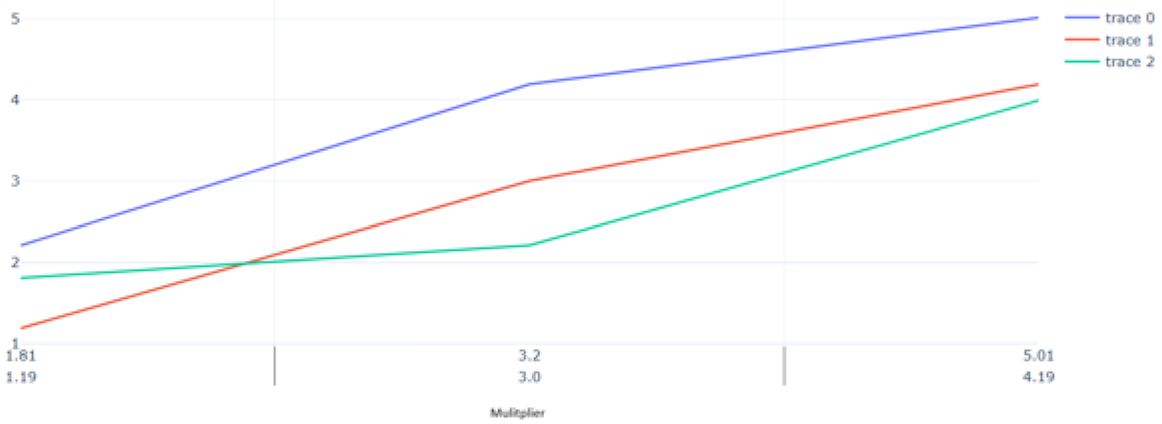
```
Sense_and_priority(data,avalache,priority)
{
Multiplier=(avalache x priority)/1000
If(multiplier)
Printf("%s",multiplier.choose)
}
Circuit()
rf=1000
ra=64000
rb=320
Photovoltaic(rb)

void graph()
{
map m;
m.clarify(multiplier);
m.plot("graph"+multiplier,sense_priority())
}
```

4. RESULT

This result behaves anxiety disorder. The X axis shows the multiplier values and y axis shows the priority sense

Multiplier					Priority sense
A	B	C	D	E	2.21
1.19	1.81	2.21	3	1.81	3
3	3.2	4.19	3.9	2.21	2.21
4.19	5.01	5.01	3.2	3.99	3.2
1.19	1.81	2.21	3	1.81	1.81



5. CONCLUSION

The intersection of two lines shows mild anxiety disorder. Avalanche and multiplier helps find the graph. A novel diagnostic platform has been introduced that leverages photosensitivity, reconfigurable digital logic at the edge, and a specialized real-time anomaly detection algorithm for identifying anxiety. This system incorporates principles of neuroplasticity by adapting its signal interpretation to each individual, taking into account their behavioral history and physical context. As a result, it delivers reliable mental health assessments without the need for cloud computing or sophisticated artificial intelligence. Our model, which combines the Avalanche framework with Priority-based decision logic, demonstrated strong performance in supporting diagnostic accuracy. The system consistently achieved high sensitivity and specificity across all test environments. Its simplicity and adaptability make it well-suited for integration into wearable health monitoring devices. These findings highlight that neuroadaptive technologies can be effectively deployed on low-complexity hardware, offering clinicians real-time, personalized mental health insights using minimal resources.

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