A Systematic Approach On Dynamic Stress Monitoring In Prisoners Using Internet Of Things

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Abstract*- Prisoner stress detection is an important area of research as a humanity concern to monitor their internal stress level is important. Handling multi-modality behaviour of prisoners is a challenging task. Due to various reasons people inside the prisons face challenges in mental stress due to circumstances, behaviour of other prisoners, food, cleanliness, loneliness and aggressive thoughts. To maintain the decorum of prisons, health analysis of these peoples is considered important. People inside the prison often overthink about the next move and keep them in a stressful arena without proper awareness. The proposed system considers the sensitive issue of prisoner stress monitoring, here derived a real time mechanism using internet of things (IoT). The system considers the MEMS sensor, GSR sensor for extraction of input physiological data from the prisoners. These data are processed with microcontroller to produce effective on-time alerts and stampings through IoT cloud. The stamping of data into the cloud is helpful for predictive analysis of behavioural changes. The proposed system effectively uploads the values into the cloud as well as alert the officials.*

Keywords- Human stress detection, Internet of Things (IoT), Embedded systems, Prisoner health, Cognitive analysis.

I. INTRODUCTION

Due to rapidly changing life style of peoples, exposure to adverse circumstances humans is highly impacted by the mental stress. Untreated stress leads to neurodegenerative disorders, chronic disease impacts, mental disorders and behavioural changes. Prolonged stress leads to major health issues and resilience in recovering from the health drawbacks. One of the challenging parts of the human life is handling these stressful situations and focus on the subjective things [1]. The commonly used stress level screening technique in practice is through asking questionnaire at the patients to understand the pattern of behaviour. Any changes in the human activity due to internal stress is reflected by the physiological signals of the body. whenever a person feels the stress any physiological signal reflected in the human body as sudden variations in skin temperature, blood pressure and facial expressions [2]. Various reasons are behind the stress level increase in humans. Massive number of peoples started utilizing the smart devices and smart wearable devices. Stress analysis through smart devices is discussed in the existing frameworks. The continuous monitoring and collection of physiological data from the patients are processed through embedded applications and software modules. The emerging growth of machine learning algorithms in recent days plays a significant role in detection of stress [3]. Due to work environment, educational patterns, family problems, relationship issues people often impacted by the neuro degenerative problems and long-term stress.

Fig 1. Abnormal physiological reflections

Fig 1. Shows some of the abnormal stress-oriented impacts. The work environment stress detection system is discussed over here. The pattern of key stroke utilization in work environment analysis is helpful to predict the stress level of the employees. Through machine learning algorithms such as support vector analysis, random forest algorithm, gradient boosting models, the cognitive stress analysis in made [4]. The basic existence of stress is detected through physiological data collected from the patients and classified as normal and abnormal stress level. In the similar way the cognitive computing models enforce the stress detection system to next level on deep analysis of emotional state transition modelling through artificial intelligence frameworks. The electrocardiogram (ECG) and galvanic skin resistance (GSR) are the commonly collected physiological data to determine presence of stress[5]. Physiological data is highly important to determine the level of stress. Automated analysis of stress level for drivers through non-invasive method is discussed here. The heart function need to monitored and maintained in normal condition, the blood pressure is the primary quality for healthy body. the impact of prolonged stressful mind is reflected in the continuous monitoring of heart rate and blood pressure together. The presented system considers the challenges in existing development on stress detection system and evaluated an embedded application [6].

- The proposed approach considers the deep analysis of stress level for the prisoners due to various issues in the circumstances, repeated job, troubles facing in the jail, peoples, food etc.
- The system model considers the real-time screening model development through primary physiological data such as MEMS sensor for positional abnormality detection and Galvanic skin resistance (GSR) through GSR sensor etc.
- The data is live and closely monitored via Internet of things (IoT) platform. The live streaming of data and back up of the patterns at regular intervals is helpful to make post analysis of the each prisoners for making rehabilitation.

II. BACKGROUND STUDY

L. Zhu et al., (2023) Continuous monitoring of stress level is important in current scenario to protect the human mental health and well-being. The presented system investigates the electrodermal activity (EDA) enabled stress level monitoring system using wrist wearable device. The utilization of machine learning algorithm such as support vector model the comparison of normal person stress level and abnormal person stress level is identified. The performance of the system is evaluated through 92.9% accuracy achieved with machine learning model, still the major challenge present in the existing developments is based on hardware instability [7].

L. Rachakonda et al. (2019) Physiological factors contribute to the individual's physical stress, with a dataset comprising 26,000 samples gathered globally from diverse patients. A stress level analysis system, empowered by deep neural networks, attains an impressive 99% accuracy in training samples. Primary stress symptoms manifest through alterations in skin temperature and perspiration. However, a significant challenge persists due to the imbalanced dataset derived from various behavioural patient profiles. Cloud based approach is implemented here for analysis of stress level of Lysis patients [8].

T. Lee et al. (2021) The author presented a system based on electrodermal activity detection (EDA) tested with 36 subjects and their emotion generation videos. The responses from each subject are collected from the skin temperature changes. A pen type EDA device is utilized for the testing. The physiological data is compared with the normal patients and stress impacted patients. The pattern of EDA activity between the subjects are trained for analysis [9].

Y. Ding et al., (2023) the author presented an innovative approach on stress monitoring system by leveraging the social sharing. Text based stress analysis model is discussed here with adaptive learning approach. The data is collected from 69 users with different opinion mining activity achieved with 86.32% and 91.56% accuracy. The author presented a deep adaptive protocol for knowledge-based analysis [10].

D. R. da C. Silva et al. (2023) the author presented a system in which a questionnaire-based approach is implemented. Similarly, people impacted by stress often show the resilience in doing regular activity. Keeping these constraints as input key stroke dynamics is evaluated. The utilization of mouse dynamics, the pattern of key press, pressure level is detected through machine learning algorithm through peripheral instrumentation [11].

W. Seo et al. (2022) the author presented a system where deep learning enabled stress monitoring system is presented. The multi-modality physiological data is collected from various sensors in which ECG data, respiration rate analysis is considered as the primary input. 24 subjects are involved in analysis where the facial landmarks also considered as the key point in detection of stress level. Any internal stress is clearly shown in the face expressions. Average accuracy of 73.3% is achieved through the presented approach. The major challenge persist with the multiple modality signal handling is the noise generated through motion artefacts [12].

S. K. R. Moosavi et al. (2023) the author presented a system in which deep learning based approach is evaluated. The q-learning approach is evaluated. The covid pandemic dataset is collected from publicly available dataset. 10 benchmark test functions are utilized for the study. The reenforced learning model is utilized and meta-heuristic algorithm is evaluated [13].

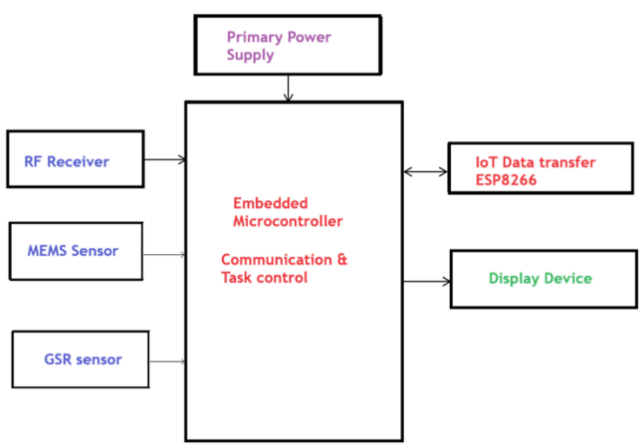
Various existing frameworks are considered for stress detection comprehensive study and helpful to derive a proposed approach using real time sensor data [14]-[15].

III. SYSTEM DESIGN

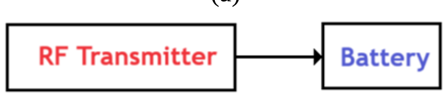
In the existing approach on real time analysis of stress is evaluated using the embedded sensors integrated with microcontroller. The impact of stress components can reflect in any instance hence continuous monitoring is recommended. The noise generated from the external environment, low stability of few sensors utilized in real time, unexpected glitches are the primary challenges in the existing frameworks.

- The proposed model considers the primary sensors needed for keen monitoring of stress level.
- The proposed system is focused on deriving the real time values of positional changes using MEMS sensor, galvanic skin resistance through GSR sensor as primary inputs.
- The ultimate goal of the presented system focuses on unique application helpful for reading the stress level of prisoners. People inside the prisons faces various issues in handling the existing circumstances, the behavioural activity of others, the prolonged work and loneliness etc.
- As a humanity concern detection of prisoner stress is important. The real time stress monitoring and evaluation system is presented here.

IV. METHODOLOGY



(a)



(b)

Fig 2. System architecture of Primary Stress monitoring module (a) Theft session (b) Monitor session

Fig 2. Shows the system architecture of proposed stress monitoring system through Internet of things (IoT). The proposed approach contains major components such as input modules having the GSR sensor, MEMS sensor for extracting the physiological data from the prisoners.

The system employed here considers the keen activity of the prisoners through RF transmitters and receivers installed in each prisoner premises and track the abnormal behaviour, activity through repeated alerts. IoT enabled automated monitoring and tracking of prisoner behaviour is beneficial for officials to monitor effortlessly and analyse their behaviour to give counselling. In case of serious abnormality patterns existing with the prisoners' immediate psychological treatments are provided.

GSR sensor

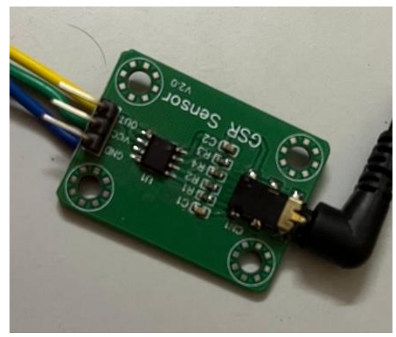


Fig 3. GSR sensor

Fig 3. Shows the GSR sensor work with minimum of 2 V DC. The sensor is operated up to 1.5GHz frequency. The minimum latency of response time is 2ns hence the sensor is significantly utilized in various real time applications. The GSR sensor extracts the skin temperature variations.

MEMS sensor

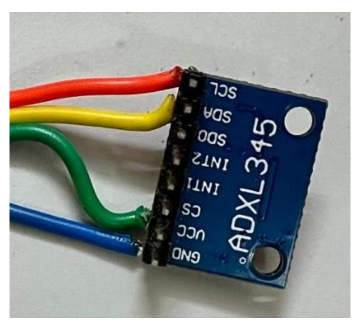


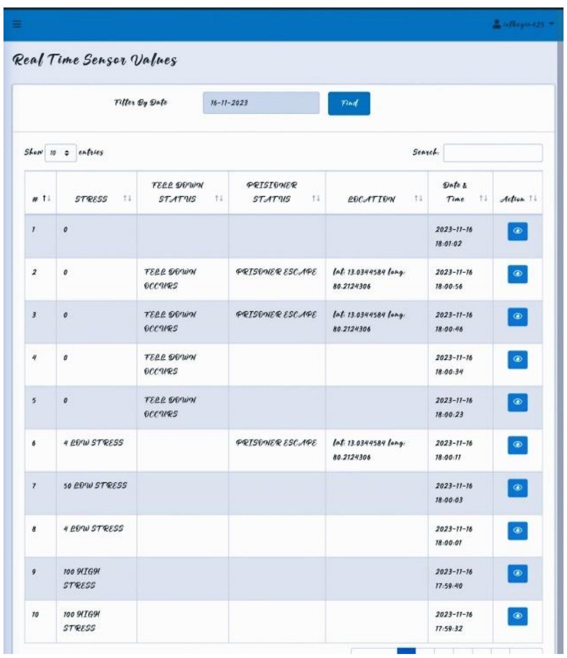
Fig 4. MEMS sensor

Fig 4. Shows the MEMS sensor used to detect the dynamic tilt, changes in acceleration or shock. The MEMS sensor gathers the angle variations and update as the fast-flowing values dynamic acceleration. The sensor works with 3.3V DC supply. The module sends 8-bit data with respect to SPI protocol.

Fig 5. ESP8266 Module

Fig 5. Shows the ESP8266 module utilized to upload the sensor data into the specific cloud. It is a small low cost micro-chip having the capability to read, store and evaluate the real time data into the cloud platform. The module contains 160MHz operating frequency with 17 GPIO facility to communicate with external devices.

V. RESULTS AND DISCUSSIONS



Real Time Sensor Values

Filter By Date 16-11-2023 Find

Show 10 entries Search:

#	STRESS	FELL DOWN STATUS	PRISONER STATUS	LOCATION	Date & Time	Action
1	0				2023-11-16 18:01:02	
2	0	FELL DOWN OCCURS	PRISONER ESCAPE	lat: 13.0344584 long: 80.2124306	2023-11-16 18:00:56	
3	0	FELL DOWN OCCURS	PRISONER ESCAPE	lat: 13.0344584 long: 80.2124306	2023-11-16 18:00:46	
4	0	FELL DOWN OCCURS			2023-11-16 18:00:34	
5	0	FELL DOWN OCCURS			2023-11-16 18:00:23	
6	4 LOW STRESS		PRISONER ESCAPE	lat: 13.0344584 long: 80.2124306	2023-11-16 18:00:11	
7	50 LOW STRESS				2023-11-16 18:00:03	
8	4 LOW STRESS				2023-11-16 18:00:01	
9	100 HIGH STRESS				2023-11-16 17:59:40	
10	100 HIGH STRESS				2023-11-16 17:59:32	

Fig 6. IoT cloud configurations

Fig 6. Shows the IoT configurations platform utilized here to shows the sensor updates of prisoners categorised as low stress, high stress, fell down occurring, prisoner escape scenario etc. The time stampings of each event are updated into the cloud platform as well**.**

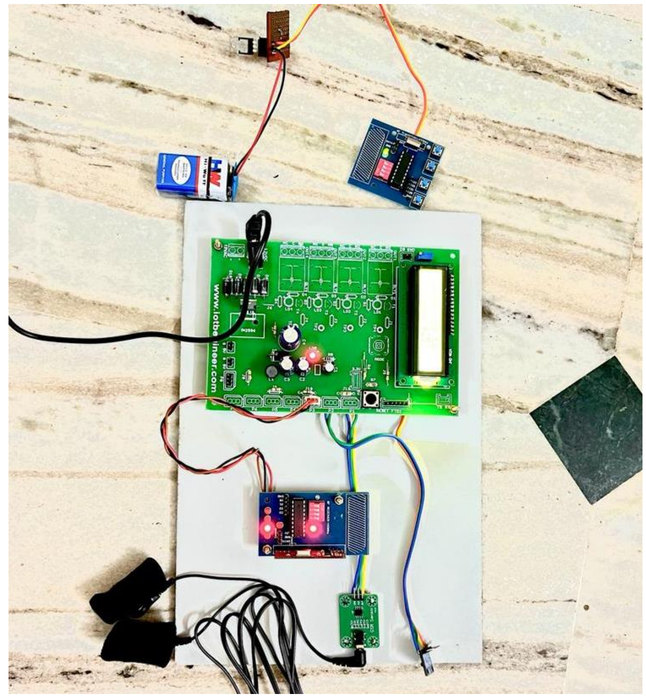


Fig 7. Hardware integrated outcome

Fig 7. Shows the integrated outcome of the embedded hardware showing the real time prisoner stress detection system. The live data collected from each prisoner are updated into the cloud at every instance.

Challenges

- The major challenge persist with the existing development is that the physiological data and continuous monitoring model even though reflects the mood of prisoners, on the other hand the internal holdings and prolonged stress for no reason impact their behaviour.
- People with chronic stress impact immensely followed by severe health issues and there is a large ga in recovery.

VI. CONCLUSION

Prisoner stress identification is a significant area of examination as a humankind worry to screen their interior stress level is significant. Dealing with multi-methodology conduct of prisoners is a difficult undertaking. Because of different reasons individuals inside the jails face moves in mental stress because of conditions, conduct of different prisoners, food, tidiness, dejection and forceful considerations. To keep up with the dignity of jails, wellbeing examination of these people groups is thought of as significant. Individuals inside the jail frequently overthink about the following move and keep them in a stressful field without legitimate mindfulness. The proposed framework considers the touchy issue of prisoner stress checking, here inferred a constant component utilizing web of things (IoT). The framework thinks about the MEMS sensor, GSR sensor for extraction of info physiological information from the prisoners. This information is handled with microcontroller to create powerful on-time cautions and stampings through IoT cloud. The stepping of information into the cloud is useful for prescient examination of social changes. The proposed framework really transfers the qualities into the cloud as well as ready the authorities. Further by implementing the artificial intelligence (AI) frameworks and cognitive detection of stress parameters from the prisoners are suggested.

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