SaYoPillow: Blockchain-Integrated Privacy-Assured IoMT Framework for Stress Management Considering Sleeping Habits

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***Abstract*—Considering today's lifestyle, people just sleep forgetting the benefits sleep provides to the human body. Smart-Yoga Pillow (SaYoPillow) is proposed to help in understanding the relationship between stress and sleep and to fully materialize the idea of "Smart-Sleeping" by proposing an edge device. An edge processor with a model analyzing the physiological changes that occur during sleep along with the sleeping habits is proposed. Based on these changes during sleep, stress prediction for the following day is proposed. The secure transfer of the analyzed stress data along with the average physiological changes to the IoT cloud for storage is implemented. A secure transfer of any data from the cloud to any third party applications is also proposed. A user interface is provided allowing the user to control the data accessibility and visibility. SaYoPillow is novel, with security features as well as consideration of sleeping habits for stress reduction, with an accuracy of up to 96%.**

***Index terms*—** Smart Healthcare, Smart Home, Healthcare Cyber-Physical Systems (H-CPS), Internet-of-Medical-Things (IoMT), Blockchain, Machine Learning, Privacy Assurance, Stress Sleep, Stress Detection, Sleeping Habits

I. Introduction

Stress is defined as a state of mental or emotional strain due to unavoidable or demanding circumstances, also known as stressors. Stress can be also be defined as a specific strain on the human body caused by various stressors. Stressors cause the human body to release stress hormones. Stressors are categorized as physiological, psychological, absolute and relative [1].

Humans develop lack of adaptation when exposed to stress due to various stressors for longer periods of time which can have major impacts on relationships, work, health and on the self by causing emotional breakdowns. Having an ability to build a self-monitoring system to tackle these stressors is very important. Incorporating these methods with the Internet of Medical Things (IoMT) creates an ease for the users to adapt. The attempt to control and monitor stress variations due to lack of sleep is the focus of this work.

The better the quality of sleep, the lower the stress levels [2]. A way to monitor and control physiological stress is presented in [3] and stress in relationship to food habits in the Internet-of-Medical-Things (IoMT) has been presented by the authors [4]. As an extension to these works, we propose SaYoPillow (see Fig. 1), where we monitor and control the stress levels of a person during the sleep period.

Fig. 1. Proposed SaYoPillow as a Consumer Electronics of e-Textile based Pillow.

In the context of IoMT driven smart healthcare, protecting patient data is an important element in smart healthcare. It is important as it requires collection, storage and use of large amounts of sensitive personal information. There were 15 million and 32 million patient records which were compromised with 503 breaches in 2018 and 2019, respectively [5]. Thus an attempt to mitigate the lack of security is also been addressed in this work.

The main motivation of SaYoPillow is to actualize the phrase "Smart-Sleeping" which can be termed as a sleep that is complete and which meets the ideal body requirements during sleep. The idea is to propose a smart wearable that requires no user input, a fully automated, response control system which does not compromise the user's convenience. It also aims to educate the user about the benefits and importance of good quality sleep and to understand the relationship between sleep and stress.

The rest of the paper is organized as follows: Section II surveys the state of the art and lists the issues with existing research. Section III explains the vision of SaYoPillow, proposed solutions and novelties. Section IV explains the relationship between stress and sleep along with its analytics. Section VI describes the training methodology used in SaYoPillow. Section V describes the stress state detection during sleep and stress state prediction for the next day. Section VII discusses the usage of the blockchain in healthcare. Section VIII presents the experimental implementation and the validation of SaYoPillow, and Section IX concludes the paper and presents possible future research.

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II. Related Prior Works and Research Gap

A. Related Prior Research and Consumer Products

The consumer electronics literature presents advancements in technologies that could be useful for healthcare applications [6]–[8]. Video advancements and 3D effects in images are proposed in [6] which can be used in image related applications. [7] also helps in improving the image quality and decrease the error rate by increasing the pixel quantity. Enhancements in automated speech recognition are another great addition as it is an important application with a potential to be used in further healthcare applications [8]. Virtual reality technology to monitor stress is proposed in [9] for better health.

A review of existing stress detection research is presented in [10]. A study shows that the muscle to muscle communication is affected whenever a person experiences stress [11]. Human stress while driving is addressed in [12]. A stress monitoring method using the data that is acquired by a smart watch is proposed in [13]. A non-invasive stress monitoring method is proposed in [14]. A stress monitoring system using cortisol as a biomarker is proposed in [15]. However, none of the articles mentioned above provide the concept of "Smart-Sleep", and do not provide stress control mechanisms or secure data transfer and storage mechanisms.

In [16], a study of sleep patterns involving participants and already existing wearables like [17], [18] is given. Few non-wearables are also available for regulating sleep [19]. However, consideration of other physiological features is neglected along with providing secure transmission and storage.

B. Issues with Existing Solutions

The major issues that are not properly addressed in most of the current research:

- Users are not educated on the importance of having a quality sleep and how it effects on stress.
- None of these works stores personal data in a privacy assured way.
- Automatic stress detection and classification methods for fully automated systems were not provided.
- Techniques to automatically control the variations of stress levels of the user are not addressed.
- A convenient stress detection wearable was not proposed.
- Multiple features to detect stress are not considered.

III. Novel Contributions of the Current Paper

A. Our Vision of SaYoPillow

Sm**a**rt-**Yo**ga Pillow (SaYoPillow) is envisioned as an edge device that may help in recognizing the importance of a good quality sleep i.e., "Smart-Sleeping", of stress variations during sleep and the following day while providing secure storage for the user's data (see Fig. 2).

B. Proposed Solution through SaYoPillow

SaYoPillow proposes a non-wearable device which is capable of:

- Automatic and continuous monitoring of physiological parameter variations during sleep with no user input.

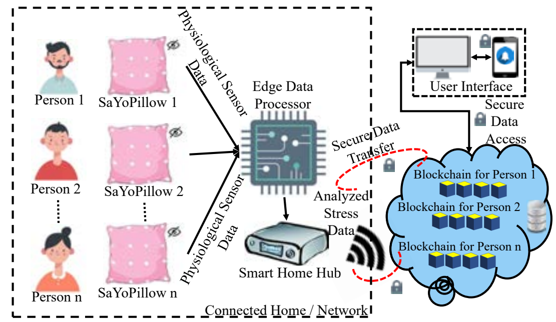


Fig. 2. Security Privacy Aware SaYoPillow in Internet-of-Medical-Things (IoMT) based Healthcare Cyber-Physical System (H-CPS) for Smart Healthcare.

- A method which educates the users to fully attain and understand the importance of good quality sleep.
- Suggesting various automated stress control mechanisms for during sleep and following day stress level predictions.
- Providing an interface to view past data and future logs to understand the stress state analysis of the user during sleep.
- Processing the information or data on the edge device while secure data storage is done in the cloud.

C. Novel Contributions of SaYoPillow

The novel contributions of this paper are:

- A continuously monitoring device which gets activated when a person is lying on a bed, for better battery life.
- An automatic stress detection and prediction method with no manual input.
- Taking the general nature of humans into consideration, proposing an automated approach which takes the time that is spent by the user on bed to drift into sleep.
- A five level status on detected stress and predicted stress based on sleep data.
- A fully-automated edge level device with secure data transfer to the privacy assured IoT-Cloud storage.
- Transferring the privacy assured data securely from the IoT cloud to the user interface for the users to obtain feedback.

IV. SaYoPillow: Proposed IoMT-Based Approach for Stress Detection and Prediction

The architecture of SaYoPillow is represented in Fig. 3. The analyzed data, with the use of Internet is securely sent to the IoT-Cloud for storage.

A. Relationship between Sleep and Stress

1) All about Sleep: Sleep can be stated as a state in which the nervous system remains relatively inactive with eyes closed and relaxed muscles as in Fig. 4 [20].

2) How to Study Sleep: To identify sleep disorders, a sleep study is conducted, known as Polysomnography. This helps in monitoring the sleep stages by performing electroencephalography (EEG) [21].

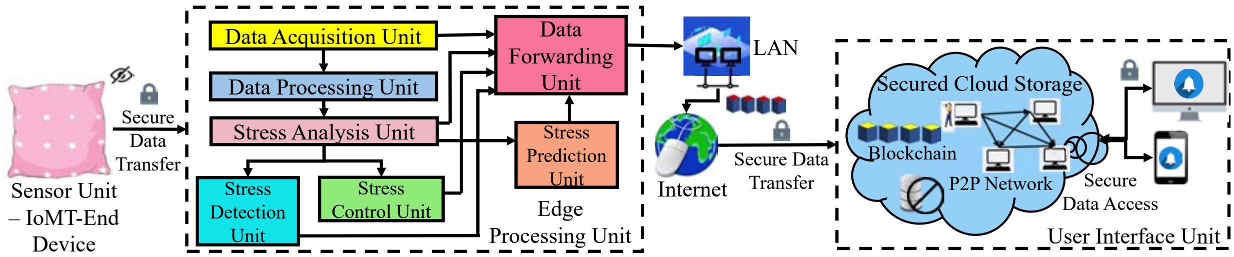


Fig. 3. Architectural View of SaYoPillow.

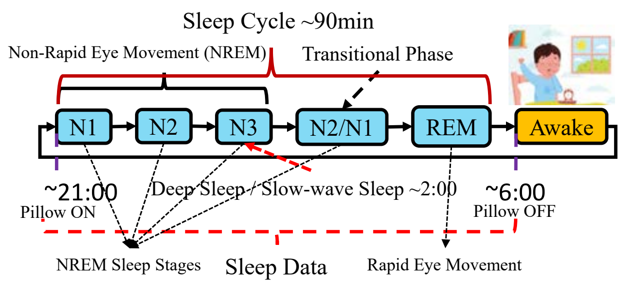


Fig. 4. Detailed Explanation of Stages in Sleep Cycle.

3) Relationship between Stress and Sleep: Studies show that the quality of sleep effects the quality of day [22]. Disturbed sleep has been associated with increased instances of sickness, burnout syndrome, persistent psycho-physiological insomnia, weak immune system, PTSD and higher risk of occupational accidents [23].

B. IoMT-Cloud Secure Data Storage with Analytics in Edge

The analyzed data at the edge processor is securely transferred to the IoT-Cloud for storage. Any third party applications that require the data, will have to securely retrieve it for not compromising the user's privacy.

V. Automatic Stress State Analysis and Control using Sleeping Habits in SaYoPillow

A. Proposed Stress Behavior Detection Mechanism

The flow of stress detection and prediction from processed data at the edge to achieve "Smart-Sleep", is represented in Fig. 5.

1) Proposed Stress States for SaYoPillow: The characterization of each state with the physiological data is discussed in Table I.

2) Stress Behavior Analysis During Sleep for Smart-Sleeping: The stress behavior of the person during sleep is performed every 15 minutes, as shown in Algorithm 1.

B. Stress Behavior Prediction for the Following Day in SaYoPillow

The prediction analysis in SaYoPillow considers factors such as sleep latency in minutes which is the length of time the user has taken to drift in to sleep, the quality of sleep and the total number of hours the user has actually slept. For

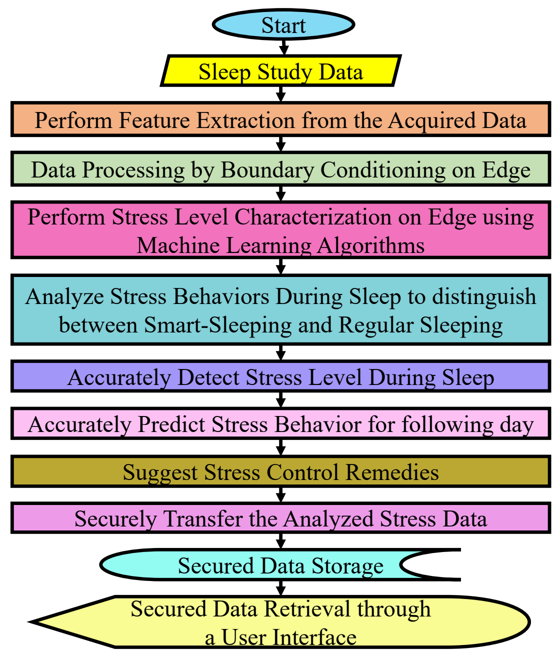


Fig. 5. Proposed Stress Behavior Analysis in SaYoPillow.

proper good quality sleep the sleep latency should be in the range of 10 to 20 minutes [24]. The analysis is presented in Algorithm 2.

C. Proposed Stress Control Mechanisms in SaYoPillow

The idea behind SaYoPillow is for the users to obtain the maximum benefit out of the natural process, sleeping. In order to face fewer health issues due to stress, an automated stress control system is proposed performing the following functions:

- Maintain the ambiance of the surroundings and environment by regulating room temperature with respect to stress level variation.
- Control the lights when the user has spent 15 minutes in the sleep latency (L) phase.
- Play sleep music or peaceful tunes directly from the phone to sooth the thoughts of the user during sleep by connecting to a phone or any other smart device.

Staying away from monitor and TV screens, taking an evening bath, performing aroma therapy or burning scented candles, reading a book, and meditating are some remedies provided [1]. Depending upon the calculated value of SP,

TABLE I
STRESS LEVEL CHARACTERIZATION WITH RESPECT TO PHYSIOLOGICAL SIGNAL DATA

Hours of Sleep	Snoring Range (dB)	Respiration Rate (bpm)	Heart Rate (bpm)	Blood Oxygen Range	Eye Movement Rate	Limb Movement Rate	Body Temperature (°F)	Stress State
7-9	40-50	16-18	50-55	97-95	60-80	4-8	99-96	Low/Normal (Healthy)
5-7	60-50	18-20	55-60	95-92	80-85	8-10	96-94	Medium Low
5-2	60-80	20-22	60-65	92-90	85-95	10-12	94-92	Medium
2-0	80-90	22-25	65-75	90-88	95-100	12-17	92-90	Medium High
<0	>90	>25	>75	<88	>100	>17	<90	High (Unhealthy)

Algorithm 1 Stress Detection During Sleep in SaYoPillow

Input: Start monitoring and gathering physiological signal data HS, SR, RR, HR, BO, EM, LM, TR and brain wave voltage BWV, and frequency - cycles per second CPS.

Output: Analyze Stress Level SL during sleep.

1 **while** $t1 \neq 0$ **do**
2   Update $t1$ at instance 1. **if** BWV == *'low'* && $t1$ == *30* && $12 < CPS < 14$ **then**
3   Start $t2$ at instance 1; user drifting to sleep.
4   **else if** $t2 \neq 0$ && BWV == *'high'* && CPS<*4* **then**
5   Update $t2$ to current value at instance 2; user in deep sleep.
6   **else if** $t2 \neq 0$ && BWV == *'high'* && $EM \neq 0$ **then**
7   Update $t2$ at instance 3; user is in REM stage.
8   **else**
9   user is in light sleep.
10   **if** $t2 \neq 0$ && BWV == *'low'* && $CPS > 13$ **then**
11   Start $t3$ at instance 1; user woke up at alert state.
12   **else**
13   Start $t3$; user woke up relaxed.
14   **if** $t1$ == *0* **then**
15   Stop monitoring and gathering physiological signal data.
16   **else**
17   Repeat steps from 6 through 20.
18 Compare the gathered data from every instance to detect SL of the user.

Algorithm 2 Proposed Stress Prediction Analysis for the Next Day in SaYoPillow

Input: Retrieve the updated variables $t1$, $t2$ and $t3$ at instances 1. Declare and initialize the variable sleep latency as $L = 0$, actual time slept to $ATS = 0$, Stress Prediction to SP.

Output: Calculate the difference between the variables $t2$ and $t1$ to update L and $t3$ and $t2$ to update ATS to predict the stress levels for the following day.

1 **while** SL *is detected* **do**
2   **if** *0.8**ATS == *'M'* | | *0.8**ATS == *'H'*| | *0.8**ATS == *'MH'* && $35 < L < 45$ **then**
3   SP == 'MH'; user could experience rapid mood swings, irritability, sleeplessness and fatigue during the course of day.
4   **else if** *0.6**ATS == *'M'* | | *0.6**ATS == *'L'*| | *0.6**ATS == *'ML'* && $20 < L < 35$ **then**
5   SP == 'ML'; user could experience some mood swings and tiredness during the course of day.
6   **else if** *0.8**ATS == *'L'* && $10 < L < 20$ **then**
7   SP == 'L/N'; user could remain active and happy for the course of the day.

the stress prediction factor, the user will be reminded through the user interface, to: [1] Stay hydrated, [2] Eat good mood food [3] Take walks periodically and [4] Display photos as notifications.

The transfer of the detected, predicted stress data is done by incorporating encryption and decryption techniques while the storage is provided by a fully secure, robust and access control blockchain.

VI. PROPOSED TRAINING METHODOLOGY FOR IMPROVING SMART-SLEEPING USING SAYOPILLOW

A. *Modeling Physiological Data for Edge Platform*

Sleep can be determined as an active period which helps in developing optimal health and well-being by processing restoration and human body strengthening. In order to monitor the quality of sleep, SayoPillow proposes real time physiological signal monitoring by considering parameters such as: (a) Number of hours of sleep, (b) Snoring range, (c) Respiratory rate range, (d) Heart rate range, (e) Oxygen in blood range, (f) Eye movement rate or duration of time spent in REM, (g) Limb movement rate, and (h) Change in body temperature.

The chances of experiencing stress and other health issues are high when the snoring rate is observed to be greater than 50dB [25]. The respiration rate is considered to be healthy if 15-17 breaths per minute (bpm) are measured [26]. When a person is sleeping, the heart beats 5-10 times slower than usual [27]. As insufficient sleep is not healthy, a minimum of 7 hours of sleep is advised to adults [28].

During the sleep transitions significant changes in the brain waves are observed [29]. A slight raise in temperature resulted in a dramatic increase of good sleep quality according to [30]. The Periodic Limb Movement Index (PLMI) which is the frequency of Periodic Limb Movements in sleep per hour of total sleep time, is 15 for 5-8% of adults and increases with age [31].

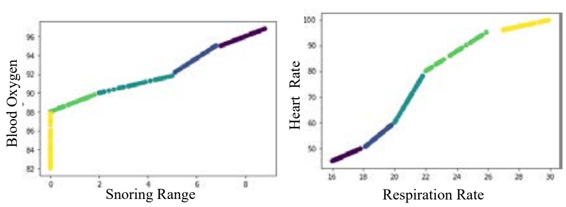
It is advised to have 20-25% of the total sleep duration in REM stage, which is approximately 90 minutes for 7-8 hour sleep [32]. Oxygen levels are considered abnormal leading to stress when they fall below 90% [33].

B. Proposed Machine Learning Based Model for SaYoPillow

In order to reduce the computation complexity and increase the efficiency a Machine Learning Neural Network Model has been trained and tested in SaYoPillow.

1) NSRR Sleep Study Dataset: For the process of training the ML Model, the dataset from NSRR is used. The study contains data taken from 6441 individuals between 1995 and 2010. Out of these, raw polysomnography data is collected from 5804 individuals [34], [35].

2) Data Processing in Machine Learning Model used in SaYoPillow: 15,000 samples were used in SaYoPillow out of which 13,000 samples are used for training while 2,000 samples are used for testing the model. The dataset is fed into the model in CSV format with approximately 3,000 samples per class. The batch size of the model to train the dataset is set as 32, as shown in Fig. 6.



(a) Blood Oxygen Vs Snoring Range (b) Heart Vs Respiration Rate

Fig. 6. Batch Representation of Data.

Here, s Fully-Connected Neural Network (FCNN) model with a linear stack of 1 input layer, 2 hidden layers and 1 output layer with 10 neurons each is used to establish the relationship between the physiological parameters and stress levels, as shown in Fig. 7.

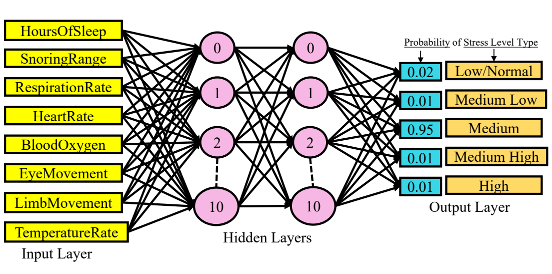


Fig. 7. FCNN Model Representation in SaYoPillow.

After the data is fed to the model, the data goes through all the hidden layers where the weighed inputs to that layer are calculated using:

$$z(X) = \sum_{i=1}^{N} (\omega_i x_i + \omega_o), \tag{1}$$

where $X = x_1, x_2, \cdots, x_n$ is the n-dimensional input, z is the response of the neuron, ω_i are the weights for each input and ω_o is a constant bias.

This produces a net input, as given in Eqn. (2) which is then applied to the activation functions to produce the output. The Rectified Linear Function is used as an activation function for the hidden layers while the Softmax function is used at the output layer. The predictions at the output layer are produced as given in Eqn. (2). When the model is trained and fed with an unlabeled example, it yields five predictions (inferences) at the output layer.

$$h_j = f((W)_j, i \cdot (x)_i + (b)_j, i), \tag{2}$$

where $(W)_j, i$ is the weight matrix, $(b)_j, i$ the bias, and f is the Rectified Linear Unit (ReLU) activation function.

For any neural network model, the loss factor is used to optimize the model. The training steps defined in SaYoPillow are represented in [3].

After this process of training is completed, the model performance is as follows:
Epoch 82100: Loss: 0.272, Accuracy: 96.667%
Epoch 82150: Loss: 0.159, Accuracy: 97.167%
Epoch 82200: Loss: 0.129, Accuracy: 96.333%

Once the model has been tested, the Testing Gradients with the specific output parameter are:
Example 0 prediction: High Stress (0.5%)
Example 1 prediction: Low Stress (0.4%)
Example 2 prediction: Medium Low Stress (1.8%)
Example 3 prediction: Medium Stress (95.7%)
Example 4 prediction: Medium High Stress (1.6%)

Finally, the loss and accuracy of the model are observed to be approximately <1% and >96%, respectively as shown in Fig. 8.

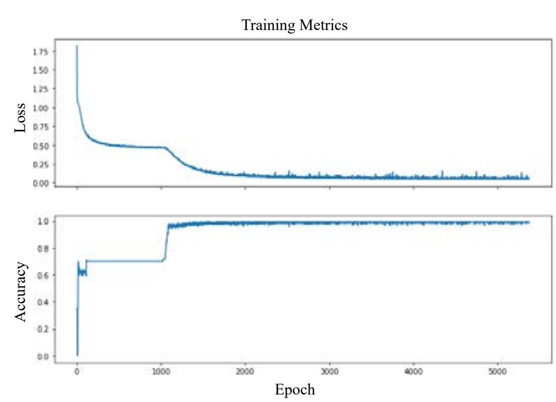


Fig. 8. Loss and Accuracy of ML models in SaYoPillow.

C. Metrics

Metrics are used to monitor and measure the performance of a model. Some of the most important metrics for any model's perfromance evaluation are accuracy, precision vs recall curve and loss. As SaYoPillow uses TensorFlow for its training model, the metrics of the model can be defined by support functions such as tf.keras.metrics.Accuracy for accuracy, tf.keras.metrics.Recall for recall, tf.keras.metrics.Precision for precision and tf.keras.losses.SparseCategoricalCrossEntropy for losses. Along with these auto generated quantities, the alternative approach of analyzing Accuracy and Confidence Interval metrics is used through Eqns. 3 and 4, respectively.

$$\alpha = \left(\frac{TP + TN}{TP + TN + FN + FP} \right) \times 100\%. \tag{3}$$

$$CI = error + / - z\sqrt{\left(\frac{(error \cdot (1 - error))}{n} \right)}, \tag{4}$$

where n is the sample size, $error$ is the confidence error and z is a critical value from the normal distribution. The detailed alternate approach used for performing this performance analyses for all the metrics including precision, recall, average precision and F-1 score is presented in our detailed version [4], [36].

VII. Proposed Blockchain based Physiological Data Storage in SaYoPillow

Physiological data are important indicators which can be included in Electronic Health Records (EHRs) for timely monitoring of the patients/individuals [37]. The blockchain is one technology which can address privacy issues and make EHR systems more robust. Blockchain can be simplistically defined as a chronological connection of blocks containing hashed transactions. Miners, special participants who have high computational capabilities will execute a Proof-of-Work consensus mechanism on the hash. PoW uses computationally hard hashing problem, which involves computing the nonce, an arbitrary value. The miner who finds the nonce first will be considered as winner and will be given the opportunity to add the new block. Miners are incentivized by awarding block rewards along with transaction fees generated from the included transactions in a block. The process is explained in detail in our paper [36].

A. Proposed Blockchain for Physiological Data Storage in SaYoPillow

Assumptions are made while proposing a blockchain architecture which are: each user will have their own SaYoPillow and will be responsible for managing their network of sensors. Every user is assigned with their own private permissioned blockchain as shown in Fig.9.

1) Data uploading from SaYoPillow: RSA encryption is used for verifying the integrity and validation of transactions for data uploads from the edge device as described in Algorithm 3.

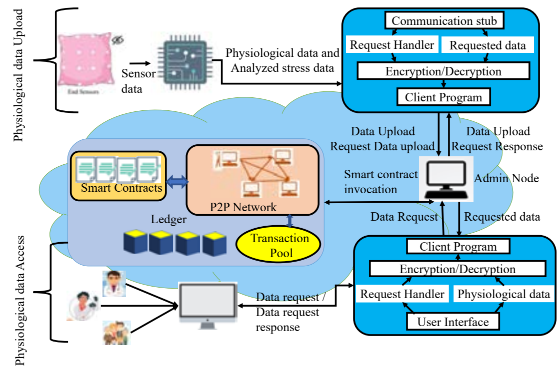


Fig. 9. Proposed Blockchain Architecture in SaYoPillow.

Algorithm 3 Process of Uploading Gathered and Analyzed Data to Blockchain

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Input: Physiological Data Transaction (PuE, PrE) and (PuA, PrA) are public and private keys of Edge node and Admin node.
Output: Result from Blockchain Update
Data: Initialization by the Edge Node
/* Receive New Data Upload Request, $TrxReq$ */
$TrxReq+ \leftarrow PuA(TrxReq||PrE(SHA-256(TrxReq)))$
  /* $TrxReq+$ is the appended signature of Egde Node and is broadcasted to Admin Node */
$PuE \leftarrow TrxReq + .getSenderPublicKey()$
if PuE == $AccessPolicyList$ **then**
  Generate Ack /* Acknowledement */
  $Ack+ \leftarrow PuE(Ack||PrA(SHA-256(Ack)))$ /* Upload Transaction Trx is created by the Edge Node */
  $Trx+ \leftarrow PuA(Trx||PrE(SHA-256(Trx)))$ /* Trx is appeneded with $PrE(SHA-256(Trx))$ and is Encrypted with PuA */
  /* Admin node verifies signature */
  if *Signature is Validated* **then**
    $BlockId \leftarrow datamanagementABI.createPhysiologicalRead()$
    Return $BlockId$:
Repeat the Process for every new $TrxReq$.

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2) Data retrieval from the Blockchain: To request information from the blockchain, an end user creates a transaction which has the requested information. Te process of data access granting is detailed in Algorithm 4.

B. Proposed Approaches for Blockchain based Secure Storage and Access

An evaluation of the proposed architecture against different attack scenarios is presented here.

Threat 1: An adversary is trying to upload tampered physiological data pretending to be the user of SaYoPillow.
Solution 1: During data upload, the edge device will add a signature using its private key to the analyzed stress data. This is again encrypted using the admin node public key. When the admin node receives an upload request, it will decrypt the data using its private key and analyzes the integrity of the

Algorithm 4 Process of Accessing Gathered and Analyzed Data From Blockchain

Input: Data Access Request;(PuEn, PrEn) and (PuA, PrA) are public and private keys of End device and Admin node.

Output: Requested Physiological Data.

Data: Initialization by the User's End Device.

/* End User generates a Data Access Request; $DataReq$. */

$DataReq+ \leftarrow PuA(DataReq||PrEn(SHA-256(DataReq)))$ /* $DataReq$+ is the appended signature of End Device Node and is encrypted with PuA and is broadcasted to Admin Node. */

$PuEn \leftarrow DataReq+.getSenderPublicKey()$

if $PuEn == AccessPolicyList$ **then**

  /* Admin Node verifies the Signature */

  if *Signature is Validated* **then**

    $RequestedData \leftarrow dagamanagementABI.RetrieveRecord()$

    $RequestedData+ \leftarrow PuEn(RequestedData||PrA(SHA-256(RequestedData)))$ /* $RequestedData$+ is sent to the End Device Node */

    $RequestedData||PrA(SHA-256(RequestedData)) \leftarrow PrEn(RequestedData+)$

    if *Digital siganture Validated* **then**

      Access Recieved Data **else**

        Discard Recieved Data

  else

    Discard Data Request

Repeat the the process for every new data access request.

message by checking the digital signature. The private key of the edge device is securely stored and is never revealed over the network, blocking the attacker from any information.

Threat 2: An attacker is trying to retrieve unauthorized information from the private blockchain.

Solution 2: Data access privileges are determined by the access-policy smart contract which has the public keys and corresponding roles. The role of the public key will determine the access privileges. As the adversary public key will not be in the access-policies, none of the data is retrieved or displayed even if a data access request is created. This provides data privacy and prevents such attackers from retrieving data.

Threat 3: An adversary is trying to retrieve useful information from the network traffic sent over the channel.

Solution 3: Once a data access request from an authorized end user is processed by the admin node, the retrieved information is encrypted with the public key of the requester end user. This encrypted information can only be decrypted using the private key of the requester end user. Private keys of the end users are securely stored where an attacker has no access. Hence, even when encrypted information is intercepted in the network channel, no useful information can be retrieved by the attacker.

Threat 4: An attack scenario is considered where an adversary has gained control over the cloud environment where the user's private blockchain is running.

Solution 4: A digital signature is added to the data and the transaction is encrypted using the admin node public key while uploading data. The received encrypted data is decrypted using the admin node private key and validates the digital signature. Physiological and stress data are encrypted again with the admin node public key before being uploaded and functions of data management are invoked, allowing no access of data.

VIII. Experimental Validation of SaYoPillow

A. Implementation of SaYoPillow using Off-The-Shelf Components

The proposed blockchain architecture for SaYoPillow is implemented in the cloud using three node Linux/Unix EC2 instances. End user devices are installed with Geth clients to retrieve and view the stress and other physiological data. Among these three nodes, one is a miner and two other nodes act as peers. The Admin node is also created in the cloud using another EC2 instance. Instances with specifications of t2.medium storage with 2 virtual CPU's and 4 GB of RAM are used in private Ethereum blockchain as nodes. Another t2.micro EC2 instance with 1 virtual CPU and 1 GB of RAM is used for admin node. The client application is installed with in the edge nodes to communicate with the Admin node.

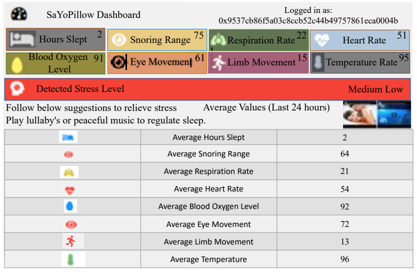
Data management and access control by the Admin node is implemented by using two different smart contracts, DataManagement.sol and AccessPolicy.sol. An access policy smart contract is used for creating different roles and to assign entities to the roles by performing functions like addRole, addBearer, removeBearer. Access modifications can only be initiated by the SaYoPillow user. Data management smart contract is implemented with functions like createPhysiologicalRecord, retriveLatestRecord, averageValues and more, which are explained in detail in our paper [36].

The Key Management System (KMS) provided by the cloud platform has been used to create Asymmetric data key pairs for the client application to interact securely. They are generated using the RSA key spec which gives both public and private keys. Data key pairs can be used for encryption and decryption of data and verifying signatures. The SHA-256 hashing function has been used to generate the irreversible digest of the data before encryption. The signature attached helps in checking the integrity of the message within the communication channel.

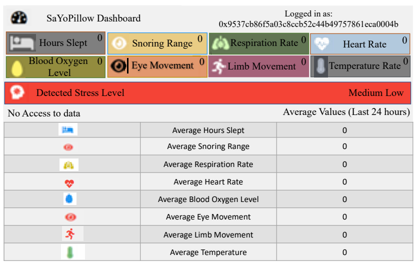
A User interface is created using html, JavaScript and web3.js [38]. For enabling the browsers to work with Ethereum enabled websites, the metamask extension is used [39]. Two different end user accounts, one of which is assigned an access role of "Family" and another without access have been used for evaluating the UI, as shown in Fig. 10. The more detailed information on secure storage mechanisms is explained in our, [36].

B. Validation of SaYoPillow

1) Validation of Stress Monitoring: For the analyzation of stress detection and prediction, an edge device on the



(a) UI with Access



(b) UI without Access

Fig. 10. Ethereum Blockchain Process and UI in SaYoPillow.

user end is used to process the physiological signal data. Even though the Dataset from NSRR has 26,688 sample files, the implementation in SaYoPillow was performed using TensorFlow with 13000 samples of data used for training and 2000 samples of data for testing. The analyzed stress levels are sent securely to the cloud for secure storage. The accuracy and loss of the models are approximately 96% and 1% as shown in Fig. 8. With the obtained accuracy, the total number of Correct Predictions were obtained using Eqn. 3. With this, the number of Incorrect Predictions are found by subtracting the correct predictions from the total predictions made. Thus, the Confidence Interval (CI), which is the probability of the detected event to fall in different stress-level classifications is observed as [0.036,0.043] using Eqn. 4.

Along with the above mentioned metrics, time complexity and space complexity are used for evaluating the performance of the model. With an approximate accuracy of 96% and CI of [0.036,0.043], the time required to complete the operation in the model is approximately 4 minutes with a bandwidth of 15000 data samples. In terms of computational time complexity, the neural network used is $O(n^4)$, where n is the total number of neurons in the model and the space complexity is $O(n)$. The stress prediction is performed at the UI i.e., the User Interface by taking in the total stress levels detected for every 15 minutes and comparing the observed stress levels as mentioned in Algorithm 2. The characteristics of SaYoPillow are represented in Table. II.

Precision and Recall are shown in Fig. 11 to help in evaluating the effectiveness and robustness of the model.

2) Validation of Stress Control: Different remedies for stress reduction are given to the user of SaYoPillow as explained in sections IV-A3 and Sec. V-C. The edge device is assumed to be capable of interacting with other devices and implementing the suggestions.

TABLE II
CHARACTERISTICS OF SAYOPILLOW

Characteristics	Specifics
Data Acquisition	NSRR Sleep Study Dataset
Data Analysis Tool	TensorFlow Lite
Classifier	FCNN
Stress level Classification	5
Total number of predictions	15000
Accuracy	96%
Correct Predictions	14400
Incorrect Predictions	600
Classification Error	0.04
Confidence Interval	0.04 +/- 0.00313

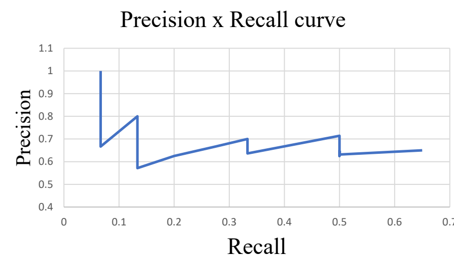


Fig. 11. Precision Vs Recall in SaYoPillow.

3) Validation of Secure Storage and Access: Transaction times (TT) are evaluated from the private SaYoPillow Ethereum network setup to the public test Ethereum network (Ropsten) and are recorded in Table III.

Mean TT's for all functions in private Ethereum instances is observed to be shorter than the public Ropsten network, as shown in Fig. 12.

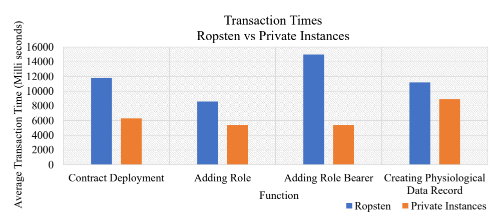


Fig. 12. Ropsten Vs SaYoPillow Network Comparison Graph .

C. Comparison of SaYoPillow with State-of-the-art

The proposed SaYoPillow has great potential of marketability by providing high accuracy and by classifying stress at multiple states. A brief comparison with other relevant works is provided in Table IV.

IX. CONCLUSIONS AND FUTURE RESEARCH

The proposed SaYoPillow not only collects and analyzes eight different physiological signal data to predict stress, but also educates the user about the benefits of smart-sleeping.

TABLE III
METRIC EVALUATION FOR SAYOPILLOW

Network	Contract Deployment: Min, Max and Avg TT (secs)	Adding Role: Min, Max and Avg TT (secs)	Adding Role Bearer: Min, Max and Avg TT (secs)	Creating Data Record: Min, Max and Avg TT (secs)
Ropsten	3.29 | 26.75 | 11.8	1.2 | 18.4 | 8.6	1.4 | 35 | 15	1.5 | 38.2 | 11.2
SaYoPillow	3.2 | 13.5 | 6.3	1.4 | 10.7 | 5.4	1.5 | 14.2 | 5.4	2.2 | 11.5 | 8.9

TABLE IV
COMPARATIVE ANALYSIS OF SLEEP QUALITY MONITORING SYSTEMS

Research	Stressors Used	ML Algorithm Performed	Features Extracted	Stress Levels Classified	Activities Considered	Performed Stress Control?	Provided Security?	Accuracy Obtained? (%)
Ciabattoni, et al. [13]	GSR, RR, BT	KNN	10	2	Cognitive Tasks	No	No	84.5
Lawanot, et al. [14]	Images and Surveys	KNN, SVM, DT	12	2	Regular Activities	No	No	83
Nath, et al. [15]	GSR, PPG	RCM	17	2	Cortisol Levels	No	No	92
Rachakonda, et al. [3]	Body Temperature, Steps taken and Humidity	DNN	3	3	Physical Activities	Yes	No	98.3
Wu, et al. [40]	HRV	KNN	N/A	2	Self Tracking	No	No	97
Rachakonda, et al. [41]	Body Temperature, Heart Rate, Snoring range and Sleep Duration	Fuzzy Logic	4	5	Sleeping Habits	Yes	No	up-to 65
SaYoPillow (Current Paper)	Heart Rate, Respiration Rate, Blood Oxygen range, REM period, Limb movement, Body Temperature, Snoring Range, Sleep Duration	FCNN	8	5	Sleeping Habits	Yes	Yes	96

Using Wi-Fi the physiological information along with stress data is transmitted securely to be stored in an Ethereum private blockchain. The work can be further extended in the specific domain of stress monitoring and control as it is an important problem that can have significant social impact.

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X. Acknowledgment

This material is based upon work supported by the National Science Foundation under Grant number OAC-1924112. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. A different version of this work has been archived at [36].

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