iMirror: A Smart Mirror for Stress Detection in the IoMT Framework for Advancements in Smart Cities

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***Abstract*—For any organization to be successful, key factors are the employees and managers working for it. If the manpower is not mentally strong, then progress may not be up to the mark. Having everything smart inside an organization won't be able to heal the mental health of employees. Healing mental health could only be achieved by smart utilization of smart infrastructure. Every individual is s**
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healthcare etc. [4]. Smart infrastructure can be observed at so many services such as parking facilities, environmental monitoring [5]–[7] which could be potentially used at work spaces and universities [8]–[10].

There is a significant improvement in the rate of adoption of smart devices, wearables and technology by humans over a period of time [11]. The smartness of a smart city is still a rough area as there is not one specific answer for how much is too smart. Along with the idea of enhancing the quality of

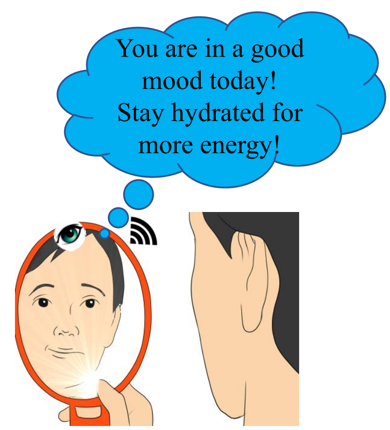


Fig. 1. Device Prototype of iMirror.

In the current lifestyle, employees, students, teachers, and employers are most effected by the pressures they experience [12] which leads to stress. Stress is considered an important factor for many chronic diseases. Prolonged stress can cause fatal diseases like cancer, anxiety, depression, obesity, PTSD, PCOS, Type II diabetes, osteoporosis, memory problems etc., [13]. For a strong foundation of smart-city, having mentally healthy employees is important, as they drive the progress. In order to address the work stress among individual before or after pandemics like COVID-19, this research proposes iMirror which analyses the stress levels of a person and gives feedback to users in order to maintain a healthy stress response system. The device prototype of iMirror is represented in Fig. 1.

The organization of this paper is as follows: Section II summarizes the existing state-of-the-art literature for emotion analysis with input images. Section III lists the novel contributions of this research. Section IV represents a broad perspective of the concepts behind iMirror. Section V represents the flow of the system. Section VI explains the model that is used for training and testing in iMirror. Section VII contains the implementation and validation details of iMirror followed by conclusions and future research in section VIII.

II. Related Prior Research

The state-of-the-art related to facial stress monitoring and detection is vast. A representative sample related to this work, along with their drawbacks is presented in Table I.

TABLE I
STATE-OF-THE-ART LITERATURE

Research	Input	Action	Drawbacks
Giannakakis et al. [14]	Video	Emotion Analysis	No User Interface, No user access, No real time processing
Liao et al. [15]	Physiological Sensor Data	Stress Monitoring	User input required, No User Interface, No user access, No real time processing
Gong et al. [16]	Images	Emotion Analysis	No Real time monitoring, no relationship with stress is established, no data visualization for user
Huang et al. [17]	Images and EEG data	Emotion Analysis	Stress monitoring is not performed, No User interface, No user access, No real time processing
Luoh et al. [18]	Images	Emotion Analysis	No User interface, No user access, No real time processing, No stress detection
iMirror (Current Paper)	Image	Stress Analysis	User Interface, User access, Real time processing, Stress detection

III. Novel Contributions

iMirror is proposed to monitor real time stress a
the user accordingly, without requiring the users t
convenience over health. The novel contributions
presented in this research are:

- A real time stress monitoring system with no u
- Provides an interface which uses real time locat
  user to provide appropriate remedies.
- A potential extension of any product that gathe
  from the user.
- A potential marketable product that can be pl
  where for monitoring purposes.
- A methodology that has the ability to address i
  control of stress.
- Visualization tools for the user for easy data co
  sion.
- Allows users to understand the fluctuations of
  get back control over their body.

IV. iMirror: A Broad Perspective Of Stress Detection Using IoMT

The broad perspective behind iMirror is discussed in this Section. The idea is for the mirror to automatically detect stress levels of the person without user input and send notifications to the user for a better stress response system. In order to understand the idea, first let us look into the impacts of stress and how facial expressions or features can define the stress state.

Stress can be defined as a reaction of the human body to a situation. Humans generally experience stress when they observe or face things which they have never experienced before, have no knowledge on what may happen next, fear of embarrassment and not having the control over the situation [19]. When in stress, the hormone cortisol is released in the human body. Such situations are called "stressors" [13].

Stress can be be classified in three different categories: acute stress, episodic acute stress and chronic stress. Acute stress is short-term, while episodic acute stress is the repetition in the frequency of occurrence of acute stress. Chronic stress is the result of prolonged exposure to stressors. When the human body experiences prolonged chronic stress, various diseases can result, such as heart disease, insomnia, depression, cancer, and burnout [13]. As an attempt to control such serious health issues Stress-Lysis was proposed based on physical activity [20]. In order to reduce insomnia, SaYoPillow is proposed by considering sleeping habits [21]. In order to control binge eating or stress-eating, wearable glasses for stress detection are proposed in [22].

Similarly, an attempt to monitor the stress level fluctuations based on facial features and expressions is made through iMirror as human beings tend to express a lot through their facial features. Generally, each expression is associated with a different emotion or sometimes a mix of emotions [23]. Thus, the broad perspective of iMirror is represented in Fig. 2. The

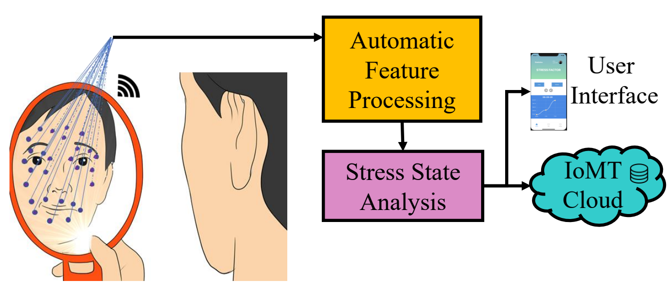


Fig. 2. Broad Perspective of iMirror.

V. Architecture for Stress Detection in iMirror

The architecture of iMirror is presented in Fig. 3. Here, the data from the camera, namely images, are taken whenever there is a person looking at the mirror. This image data is sent to a single board computer (SBC) for automatic data processing. After the data is processed the SBC then analyses the stress levels of the user. The analyzed information is sent to the cloud for storage and is also sent to the user interface for easy access by the user.

The system level modeling of iMirror is as follows: the input image data is taken from the camera and sent to the SBC which could be located on-site or located remotely and be a part of the network. The object classification is performed using graphical annotation tools followed by feature extraction by segmenting the background data. From there, the objects or features are detected and are then considered for the stress state analysis of the user. The SBC is connected with a cloud platform which hosts the database. The database is connected to the mobile application which is used as a user interface in iMirror. The flow of the modeling is represented in Fig. 4.

VI. Proposed Methodology of iMirror

The proposed method for stress detection using iMirror is represented in Fig. 4. The automatic data processing module performs object classification from the image followed by detection of the classified object. After that the stress level is characterized depending on the confidence interval of each detected object, followed by analysis. The analyzed data is sent to the user for examination.

A. Object Classification

As the input images are obtained, the required or the interesting portions from the total image are obtained by using graphical annotation tools. If, in some images, there is another random object that is covering the desired object or the object of interest, image subtraction tools are used which will suppress the initial errors thereby segmenting the background object. A mapping function is used to restore the original image when required.

B. Object Detection

The images are segmented to groups of pixels for better detection after the classification. This process is called segmentation. There are many techniques which can be used for the process of segmentation. They are thresholding, converting a grid of pixels to binary standards, searching for a variance difference of two pixels classes or by using Gaussian noise filter for edge detection. The pixels which belong to the same segment are arranged together through bounding box technology which is one of the many methods which cluster the data set by finding a principal set of dimensions. These boxes are used to reduce pixel group size and coordinate vectors.

A machine Learning model is used for the process of classification and detection through an object detection API. Pre-Labeled images are used for assessment of a classification program also known as training in the model. In the learning stage of model, a multi layer topology of nodes with weights and bias values is considered. For every layer i in the model its values $(x)_i$, weight $(W)_j, i$, bias $(b)_j, i$ and activation function f are provided which are used in predicting the values of next layer j with its corresponding values $(h)_j$ as in Eqn. 1:

$$(h)_j = f((W)_j, i \cdot (x)_i + (b)_j, i), \tag{1}$$

Algorithm 1 Stress Level Characterization

1: When there is a person observed in front of the mirror by motion sensor m, declare and initialize a input variable id and timer t to zero.
2: Initialize the confidence values of feature variables r, e, d, f, s to zero.
3: Initialize the output variable sl to zero.
4: **while** m ! = 0 **do**
5:    Update t and id.
6:    Update r, e, d, f, s.
7: **end while**
8: **if** 80% < = r, e, d, f, s < = 100% **then**
9:    Update sl to High (3).
10: **else if** 60% < = r, e, d, f, s < = 70% **then**
11:    Update sl to Medium (2).
12: **else if** 50% < = r, e, d, f, s < = 60% **then**
13:    Update sl to Low (1).
14: **else**
15:    Update sl to Normal (0).
16: **end if**
17: **while** m ! = 0 'and' id == id **do**
18:    Update $id1$ ++ and $t1$ ++.
19:    Repeat from Steps 2 through 16.
20: **end while**

C. Stress Level Characterization

The characterization of the features with respect to stress is discussed here. Whenever a person is captured by the camera, the corresponding person is assigned with a unique identity. The detailed flow of characterization assuming single user is presented in Algorithm 1. The features which are considered in iMirror are Eye redness (r), eye bags (g), pupil dilation (d), frown in forehead (f) and facial sweat (s).

This characterized information is then sent to the stress state analysis unit.

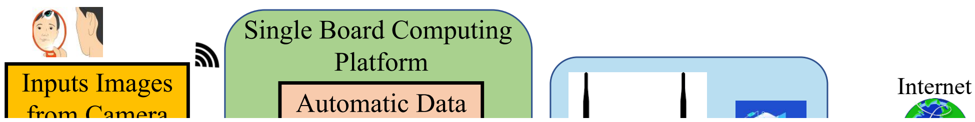
D. Stress Level Analysis Unit

The stress state analysis is assumed to be updating the complete days stress levels of the person at the end of the day. The analysis is based on the characterization of stress. The stress is updated every one hour through the mobile application. The flow of this analysis is represented through Algorithm 2.

E. Metrics for iMirror

The metrics considered for the model are its Precision, Recall, Accurate Precision (AP), and Confidence. The basic metric constituents such as True Positive (TP), False Positive (FP), False Negative (FN) and True Negative (TN) are as follows:

- True Positive (TP): A correct detection.



System level

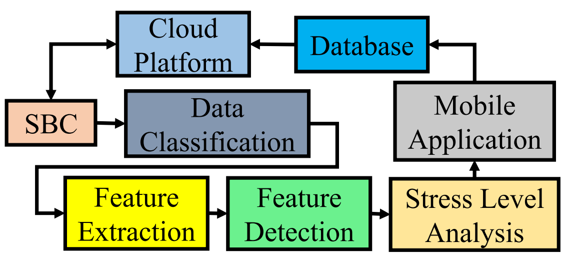


Fig. 4. System Level Modeling for Stress Detection in iMirror.

Algorithm 2 Stress Level Analysis

Declare and initialize final stress fs to zero.
Take the updated sl, t and id.
Declare and initialize the variable nt for number of iterations of t.
if $id \; != 0$ **then**
  if $t == 0$ **then**
    Update fs.
  else
    Compute Sum for sl at all t and store it in fs.
    Divide fs with nt.
    Update fs.
  end if
end if

- False Positive (FP): A wrong detection.
- False Negative (FN): This occurs when a ground truth is not detected.
- True Negative (TN): This is the possible outcome where the model correctly predicts a ground false. This is not considered in object detection classifiers because there are many possible bounding boxes that should not be detected within an image.

1) Precision: The ability of a model to identify only the relevant objects from an image is known as its precision (P):

$$P = \left(\frac{TP}{TP + FP} \times 100\% \right). \tag{2}$$

2) Recall: The ability of a model to identify all the relevant cases from the detected relevant objects is called recall (R):

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

3) Confidence: Confidence is used to rank the predictions and quantify the relationship between prediction and recall as we consider increasing numbers of lower ranked predictions. Instead of presenting a single error code, a confidence interval CI is calculated:

$$CI = z\sqrt{\left(\frac{\alpha \cdot (1 - \alpha)}{N_{sample}} \right)}, \tag{4}$$

where N_{sample} is the sample size, z is a critical value from the Gaussian Distribution, and α is the accuracy obtained.

4) Accuracy: The accuracy of a model can be defined as the ratio of correct detection made by the model to all the detection's made by the model:

$$\alpha = \left(\frac{TP + TN}{TP + TN + FN + FP} \right) \times 100\%. \tag{5}$$

VII. Implementation and Validation of Stress Detection in iMirror

A. Machine Learning Model for iMirror

The camera on the mirror will capture images with the help of a motion sensor which will trigger whenever a person is located. This JPEG data, through Wi-Fi connectivity will be sent to the SBC that is used for feature classification and detection. This data is sent to the stress state analysis unit which will update the stress values accordingly to the mobile application through a cloud platform and database. iMirror considers 5 classes of data for this initial version. The model has been trained with 1000 images. Out of these 1000, 800 have been used for training the model and the remaining 200 have used to test the models confidence rates. All these images have been taken from copyright free open source websites such as Pixabay, and Freepik.

The model that has been used here is SSD (Single Shot MultiBox Detector) Mobilenet as this is the only one that has the capability of working in a lightweight version. For the tool, TensorFlow object Detection API has been used. The prompt with 33289 steps and 9704 learning is represented in Fig. 5

• TensorFlow Lite Implementation

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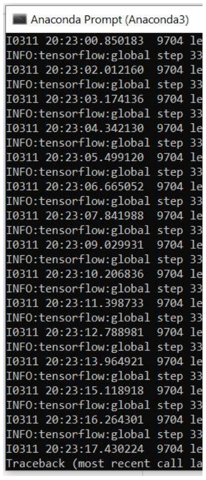

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Fig. 5. Training Mod

The model implementation with confidence rates is represented in Fig. 6. The confidence rate for various classes of

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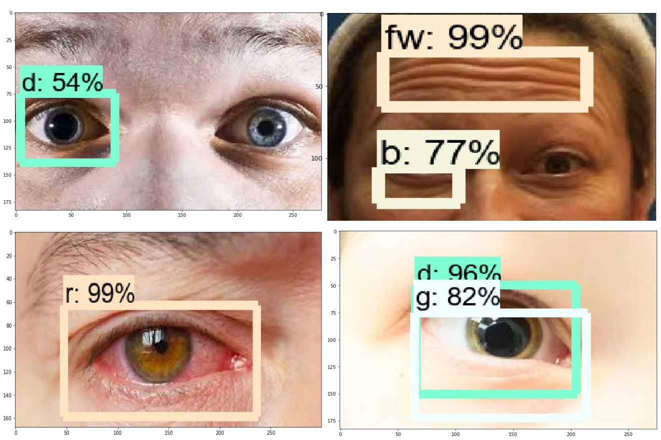

Fig. 6. ML Model Implementation with TensorFlow in iMirror.

TensorFlow Lite is a reduced lightweight version of TensorFlow which is focused on mobile and embedded devices applications. The iMirror model has been implemented with TF-Lite as this produced a higher frame per second (FPS) rate and is feasible for extending the application domain to Android or any other mobile platform in the future. For training and testing 350 images were used, out of which 280 images were used for training while 70 are used for testing. The implementation of the model on the SBC is shown in Fig. 7.

A comparison of results for 15 epochs with 5 cross validation and 5 times repeated 5 cross validations are represented

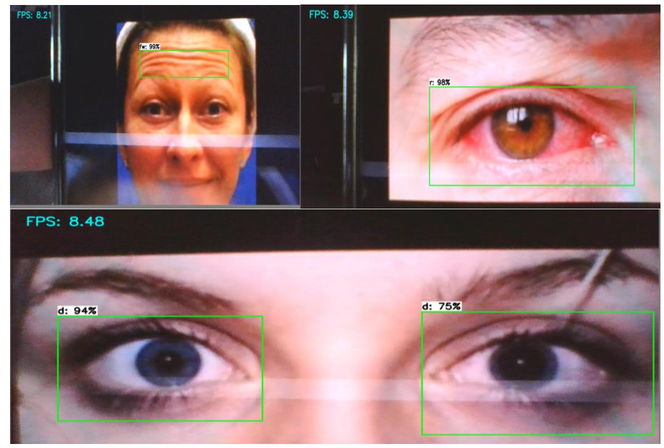

Fig. 7. ML Model Implementation on SBC with TensorFlow in iMirror.

in Table II. The change in percentage can describe that given more training data, the more accurate the results.

TABLE II
ACCURACY RESULTS FOR STRESS DETECTION IN IMIRROR.

Feature	CI(%) for 5 fold cross validation with 15 epochs	CI for 5 Repeated 5 fold cross validation with 15 epochs
Facial Sweat	88	96
Eye Redness	89	97
Forehead Frown	88	94
Pupil Dilation	89	97
Eye Bags	85	93

B. Implementation of the Model from SBC to User Interface in iMirror

After the stress detection and analysis is performed, for the user to access the information, the data from the SBC is sent to the mobile application. The SBC is connected to the cloud platform which is again connected to the database. This database is connected to the mobile application simulator where the application was built, as shown in Fig. 8. The tools which were used in developing this mobile application are React Native, Firebase Cloud Services, Tailwind CSS, Expo, React-native-chart-kit along with Visual Studio Code and iOS Simulator.

C. Validation of Stress Control Remedies in iFeliz

The characteristics that are used in the implementation of iMirror are summarized in Table III.

The specifications of the model along with its implementation type is presented in Table IV.

D. Comparison of iMirror with the State-of-the-Art

A brief comparison of the existing literature to iMirror is represented through Table V.

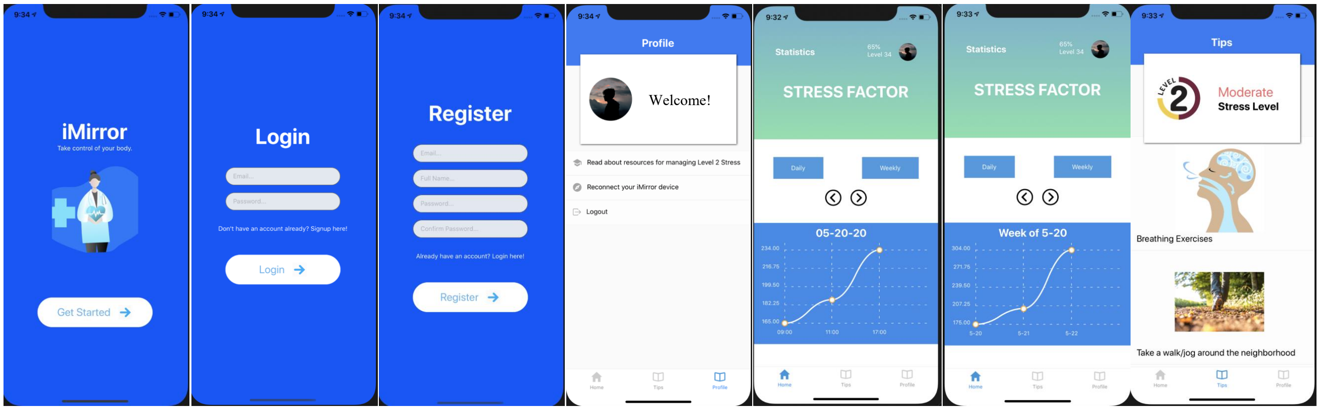

Fig. 8. Mobile Application as an UI for users in iMirror.

TABLE III
CHARACTERISTICS OF IMIRROR

Characteristics	Specifics
Input System	Images (JPEG) from Camera
Data Acquisition	Database and API approach
Data Analysis Tool	TensorFLow and TensorFlow Lite
Graphical Annotation Tool	LabelImg
Input Dataset	1000 and 350 images
Classifier	SSD MobileNET
Features Considered	6
Accuracy	97% and 98% on single board platform

TABLE IV
SPECIFICATIONS OF IMIRROR MODEL

Characteristics	SBC
Camera	5MP; 640x480
Accuracy	987%
Average Precision	81.2%
Object Detection	Yes
Object Classification	Yes
Stress Level Characterization	Yes
Input Type	Image
Automation	Fully Automated

TABLE V
COMPARATIVE ANALYSIS OF IMIRROR WITH THE STATE-OF-THE-ART LITERATURE

Research	Input	ML Algorithm	Features Extracted	Stress Levels	Accuracy (%)
Kolodziej, et al. [24]	Images	KNN, SVM, BT	6	No	52.8, 55.9, 57.7
Rachakonda, et al. [22]	Images	SSD Mobilenet	4	2	98
Tarnowski, et al. [25]	Images	KNN, MLP	7	No	73
Rachakonda, et al. [20]	Physiological Data	DNN	3	3	98.3
Du, et al. [26]	Images	KSDA	7	No	83.2
Luoh, et al. [18]	Images	GMM	N/A	No	90
Rachakonda, et al. [21]	Physiological Data	FCNN	8	5	96
Huang, et al. [17]	Images	KNN	N/A	No	N/A
iMirror (Current Paper)	Images	SSD Mobilenet	5	4	97

VIII. CONCLUSIONS AND FUTURE RESEARCH

iMirror has good potential to become a marketable device as there are not many products that relate facial feelings to stress. The use of a single board computer allows for extensions as it can be placed anywhere without having specific restrictions. The model that has been trained for iMirror is SSD Mobilenet which is a great foundation allowing iMirror to broaden its scope of applications. The accuracy was approximately 97% with an average precision of around 81.2%. The mobile application which allows user access plays a major role as potential control remedies could be added to the framework for much better performance.

The broad adaptation of iMirror is what we aim through this research as iMirror could be an important component among employers and employees thereby allowing the mankind to have healthy stress response systems. By allowing the people to have a stable mental health, iMirror strives to achieve the true state of "Smartness" for any Smart-City.

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