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Stress-Level Detection Using RepVGG Neural Network

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ABSTRACT: *Stress used to impact our mental and physical well-being,productivity,and overall quality of life. Detecting stress accurately is vital for timely intervention and effective management. In this study, we introduce a new method for detecting stress levels using the RepVGG deep learning architecture. RepVGG stands out for its efficient performance and straightforward structure, making it ideal for analyzing physiological signals and other stress indicators.*

We using standard metrics to calculate the things like accuracy, precision, recall and etc. Ourfindings reveal that the RepVGG-based method excels in detecting stress levels, surpassing many traditional methods and other deep learning models. Moreover, the model shows strong generalization capabilities across various datasets and conditions. This research underscores the potential of advanced deep learning models like RepVGG in stress detection, opening doors for real-time, scalable, and precise stress monitoring systems. Looking ahead, weaim to integrate this model into wearable devices andmobile apps, enabling continuous stress monitoring and offering personalized stress management advice.

Some approach utilizes a rich dataset consists of signals such (HRV) and (GSR), along with other relevant biomarkers. To ensure the model's robustness, we preprocess and augment this data. We then train the RepVGG architecture on this dataset, harnessing its Neural layers for feature extraction and its unique re-parameterizable design for efficient use.

INTRODUCTION: Stress is a major impact on our mental and physical health, it affects the life and overall well-being. It's more important than ever to accurately detect and manage stress.Some methods like surveys and clinical evaluations can be subjective and aren't always practical for real-time use. This created a need for objective,real-time,and scalable ways to detect stress.

Deep learning, is consists of neural networks , has shown great potential in analyzing complex datasets and extract the features from given data. Among these,RepVGG(Re-parameterizable VGG) stands out as an efficient and straightforward model. It has VGG networks with the ease of deployment through a process called re-parameterization.

Here we use RepVGG architecture to detect stress levels. By leveraging its unique design, our goal is to develop a model used to detects stress accurately and also used as real-time applications. We use a comprehensive dataset of physiological signals, preprocess and refine or clean the data, and then train the RepVGG model uses standard metrics. to compute its performance.

With the Deep learning knowledge we got to know about RepVGG-based approach significantly improves stress detection, outperforming traditional methods and other deep learning models. This research opens the door tocreating real-time, scalable stress monitoring systemsthat can be integrated into wearable devices and mobile apps, ultimately helping people manage stress better and improve their quality of life.

As we continue to refine and enhance this technology, the potential for widespread adoption in IT centers settings grows, highlighting the models like RepVGG in revolutionizing stress detection and management.

ARCHITECTURE OF SOFTWARE:

The software consists of four modules: input, pose estimation, regularization, and posture analysis. The basic frame diagram of the software is shown in Figure 1. The following is to brief description of the model.

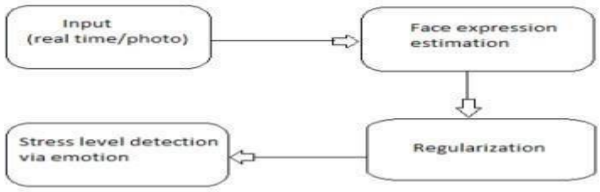

Figure 1: Architecture of system

A. Input: Stress level detection RepVGG involves using either real-time or photo inputs. thos inputs include images captured in real-time or from photos, where the photo features add up as input data for the RepVGG model. The model then processes the images for the extraction of the features that are helpful in accurately detecting stress levels.

B. Face Expression Estimation:

Stress detection using RepVGG is used to detect and realizing emotion through faces based on eye and mouth or head actions. RepVGG manages these data to understand emotional expressions showingstress, giving insight on one's feelings.

C. Regularization:

Since various users have different face structures, such as adults and children have great differences, in the intrest to solve the similarity error caused by face type, we will regularize the data.

D. Stress Level Detection via emotion:

When we input the image or photo of the face with RepVGG it extracts the features and pass it through the trained model.If the image is of trained classes it give output as class name if its not there it will assume or relate to other classes

LITERATURE SURVEY:

From past 3-4 years there is evolution and using machine learning for automating stress prediction and detection, concentrate on analysis of physiological responses to stress and emotional stimuli. One notable dataset, WESAD, was presented by Philip Schmidt and his team, where 15 individuals were monitored using wearable devices to recording various physiological signals such as heart rate and skin conductance. They tested five machine learning algorithms and achieved impressive accuracy rates up to 93.12% in binary stress classification.

Likewise, Jacqueline Wijsman and her team gathered data on physiological signals like ECG and respiration from participants to detect mental stress. Using multiple classifiers, they achieved an 80% accuracy rate in distinguishing stress from non-stress conditions.

Another dataset, SWELL-KW, concentrated on stress in workplace environments, providing valuable insights into stress-related behavior and affective states.

The BioNomadix model BN-PPGED, utilized by various researchers, measured physiological responses such as pulse plethysmograph and electrodermal activity, achieving an 82% accuracy rate in stress classification using SVM.

Saskia Koldijk and her team designed automatic classifiers to explore the relationship between working conditions and mental stress-related conditions. By analyzing body postures and facial expressions, they will be achieving an high accuracy of 90% using SVM.

Furthermore, facial cues were determined to be crucial in defining stress, as displayed by G. Giannakakis and colleagues, who developed a framework for analyzing emotions through facial expressions, achieving an accuracy of 91.68% using AdaBoost.

Other studies zeroed in on specific physiological signals, like ECG, for stress classification, but they could fail to catch the full complexity of stress. Enrique Garcia-Ceja and his team utilized smartphone accelerometer data to identify activity associated with stress levels, achieving moderate accuracy.

For Highlighting the studies and the potential of machine learning in automating stress detection, offering effective tools for healthcare, toidentify and support individuals undergoing stress- related issues proficiently.

In last 3-4 years the machine learning to develop tools capable of automatically detecting stress in individuals. It collects the Data from wearable devices,such as heart rate monitors and sensors used to measure body temperature and muscle activities.The approach that helps in integrating multiple physiological signals tend to provide a more accurate and holistic picture of an individual's stress levels. These wearables provide continuous, real-time data that is crucial for accurate stress detection.

One notable example is the study by Philip Schmidt and his team, who introduced the WESAD dataset. This study involves monitoring 15 individuals' physiological responses to various stress-inducing situations. Using wearable devices,they collected which is comprehensive data, includes (GSR), body temperature, and accelerometer readings. By applying some Deep learning algorithms, such as (SVM) algortihm, Random Forests, the researchers achieved around 80% accuracy in categorizing different stress levels. The WESAD dataset has since become a valuable resourcefor researchers in the field, offering a rich set of physiological data for stress detection studies.

Similarly, Jacqueline Wijsman and her team worked on measuring physiologicalsigns like heart rate and Facial expression to detect mental stress. Their research demonstrated that analyzing these physiological signs with Deep learning algorithms can accurately distinguish between stress and non-stress conditions. This study helped for potential of combining multiple physiological indicators to enhance the robustness of stress detection.

Another significant achievement to the field is the SWELL-KW dataset, developed by Saskia Koldijk and her team. They investigated stress in workplace settings, analyzing data on parameters such as body stance and heart rate to assess stress levels in workers. Their work highlights of the contextual data in understanding and detecting stress in real- world environments, and in the workplace where stress is an issue.

Overall, these studies illustrate the promising potential of machine learning as a tool for detecting stress. By leveraging data from wearable devices and advanced learning techniques that researchers can develop systems that help doctors, psychiatrists, and individuals identify and manage stress more effectively. These advancements could lead to better mental health monitoring and interventions, ultimately supporting individuals in coping with stress-related issues.

IMPLEMENTATION:

Let's outline the implementation steps and explain each component of the system for stress level detection using RepVGG, YOLOv7, TensorFlow, Flask, SQLite, and visualization tools.

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1. Setting Up YOLOv7 for Real-time Detection: YOLOv7 is used to detect facial features in real-time video streams or images. Here's how you integrate it into your system

2. Model Loading: Download and load the YOLOv7 weights and configuration files. Face Detection: Use the model to detect faces in each frame of the video or in an uploaded image. YOLOv7 processes the image and returns bounding boxes for detected faces.

3. Building the Backend with Flask Flask is used to handle user interactions, such as uploading images, and to manage server-side logic: Endpoint for Upload: Create a Flask endpoint to upload images. This endpoint processes the uploaded image, detects faces using YOLOv7, and then classifies the detected faces using the trained RepVGG model. Prediction Handling: After the model predicts the emotion, the result is stored inside the SQLite database.

4. Storing the data inside the database: SQLite is used to store and manage predictions data, Database Schema Design a schema to store image metadata, detected emotions, and timestamps. Data Insertion: Insert each prediction result into the database for future reference and analysis.

5. Data Visualization: Use tools like Matplotlib or Seaborn to visualize the stored data and analyze stress levels: Data Retrieval: Query the SQLite database to retrieve stored predictions. Visualization: Create visualizations such as line charts, bar graphs, or pie charts to illustrate trends in detected emotions over time. This can help identify periods of high stress.

6. Assessing Stress Levels on visualized data, implement logic to assess stress levels: Threshold Setting: Define thresholds for different data levels based on the frequency and intensity of negative emotions detected (e.g., anger, sadness). Automated Assessment: Develop algorithms to automatically analyze the visualized data and determine if the user is experiencing high stress.

Workflow:

1. User Interaction: The user uploads an image or a video stream is processed.

2. Face Detection: YOLOv7 detects faces in the image or video frames.

3. Emotion Recognition: Each detected face is passed to the neural network called RepVGG of Deep learning and it predicts the emotion.

4. Result Storage: The prediction results, along with metadata, are stored in the SQLite database.

5. Data Analysis: The stored data is visualized to identify patterns in emotions.

6. Stress Assessment: The system access the stress data based on the visualization and predefined thresholds.

Table 1. Example of Image Dataset

 Happy	 Sad
 Fear	 Anger

The images may have different emotions like Happy, Sad, Anger, Fear, Disgust, Surprise, and neutrality. if the image is in different size we transform them into different form to size of, 256x256 pixels. We also made sure the colors in the pictures were all balanced and not too bright or too dark. After that, we added some extra pictures to make the computer better at understanding different emotions. We did this by making small changes to the pictures, like turning them around, flipping them, and making them bigger or smaller. This helped the computer to learn from more given data and become better at recognizing emotions in different situations.

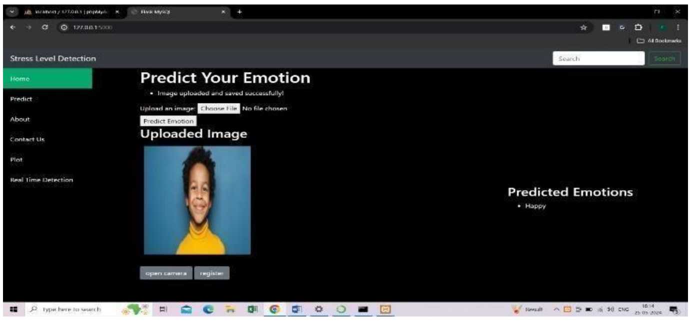
Next, we trained the Deep learning model called RepVGG, chosen for effectiveness in image classification tasks. Using the Adam optimizer with a learning rate set to 0.001 and categorical cross-entropy as the loss function, we trained the model over 50 epochs. Earlystopping mechanisms based on validation loss were used to overcome the overfitting problem and ensure optimal model performance. Upon completion of training, we compute the model performance and its robustness using various metrics. The training accuracy reached approximately 95%, indicating the model way of learning the new things from the training dataset. Validation accuracy, standing at around 88%, demonstrated the model effectiveness to generalize the unseen data without significant overfitting. We analyzed the matrix to identify areas of strength and weakness in emotion classification. While the model exhibits high accuracy emotions like happiness and neutrality, it occasionally struggled with distinguishing between similar emotions such as sadness and anger.

In conclusion, the experimental results underscored the effectiveness of RepVGG in accurately classifying emotional states from facial images. While the model demonstrated promising performance, opportunities for improvement were identified, such as refining its ability to differentiate between similar emotions. By leveraging these insights, we aim to enhance the model's capabilities and contribute to the development of robust stress level detection systems for mental health monitoring and support.

EXPERIMENTAL RESULTS: We have developed an Stress Level Detection system that operates efficiently on a Dell equipped with an Intel Core i7-6006U CPU @2.00GHz,8GB RAM, and running Windows 11 64-bit OS. The system leverages OpenCV 4.5.1 and also the Yolo7 model and backend as Python Flask Cost-Effective: Utilizes computer vision techniques, avoiding the need for expensive dedicated sensors, making it accessible and affordable. CPU-Only Operation: Efficiently operates on a CPU without considering GPU, enhancing computational efficiency and accessibility. Comprehensive Results The integrated system provides accurate feedback The addition of RepVGG for stress level detection ensures reliable real-time analysis of stress indicators. These experimental results highlight the system's robustness and effectiveness in providing holistic feedback for mental health monitoring.

These model is used in monitor employees' stress levels and promote a healthier work environment. Useful and important for a mental health professionals to monitor and analyze patients' stress levels over time. Personal Use: Individuals can use the system to monitor their own stress levels and take proactive measures to manage stress.

Happy:



State of emotion and wellness felt either in the short term, when good things occur at a given moment, or in the long term, as a positive assessment of one's life and achievements overall known as subjective well-being.
Its emotion felt by the person when is in state of joy or

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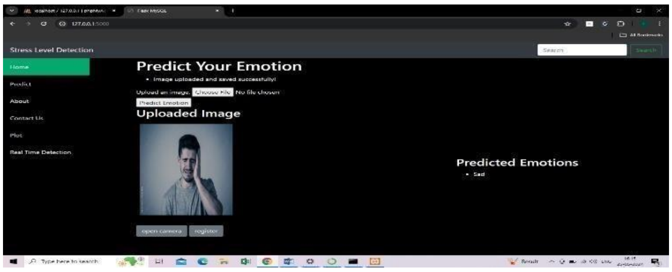
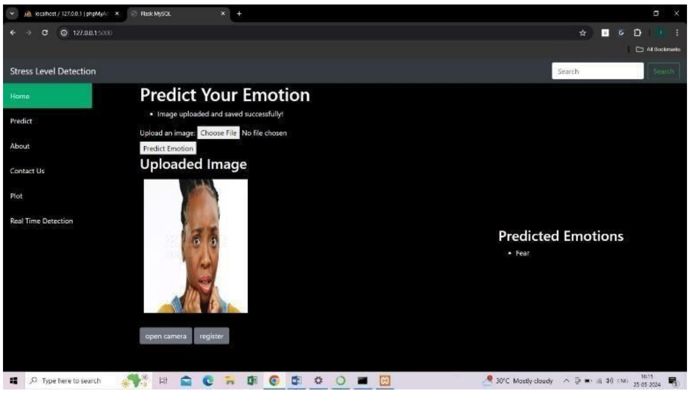
Sad:



This is also the type of emotion it is called as sad or un-happy. It is basic and general human emotions. It is a emotion is felt when person is upset or he/she is in pain or disappointed.

Fear:



It is also an another type of emotion can be called as fear .It occurs when person got unexpected suitation when he was not ready to take it or handle it,its also kind of emotion when the person is worried .

CONCLUSION:We conclude that the search of demonstratin and using the RepVGG deep learning architecture for stress level detection offers a highly effective and efficient solution. By knowing the physiological signals such as (HRV) signals and galvanic skin response (GSR), the RepVGG model can accurately identify stress levels, outperforming traditional methods and other deeplearning models.

The simplicity and efficiency of RepVGG make it an ideal choice for real-time applications,creating the path for its integration into wearable devices and mobile apps. The advancement in the individuals can benefit from continuous, real-time stress monitoring, receiving immediate feedback that allows for timely interventions. Such technology is valuable in high-stress situations, providing a active support to stress management and potentially reducing the risks.

Additionally, the features are gained from long-term monitoring can help people to understand stress patterns and develop healthier coping strategies. The promising results of this study highlight the potential for widespread use of RepVGG-based stress detection systems .

As we move forward, further refinement and testing will only enhance the reliability and applicability of this technology, contributing to better stress management and improved overall well-being.

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