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Facial Expression Based Stress Detection Using Deep Learning Algorithm

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Abstract

Stress is a growing concern in both academic and professional environments, affecting the mental well-being and performance of students and staff. Traditional methods of stress detection, such as surveys or interviews, may not always be timely or accurate. This project proposes a deep learning-based approach to detect stress through facial expressions, offering a non-invasive, real-time solution. By using computer vision and neural networks, facial features are analyzed to identify emotional states that indicate stress. The system can be integrated into educational or workplace settings to help monitor individuals' emotional health, enabling early intervention and support. The goal is to create a smarter, healthier environment that promotes mental well-being and productivity.

Keywords: Stress Detection, Emotion, Facial Expression Classification, Convolutional Neural Networks.

1 Introduction

The demanding nature of modern academic and professional environments can lead to stress among students and staff, often with significant consequences. Heavy workloads and performance pressures can result in mental strain that may go unrecognized. Early detection of stress is essential for maintaining emotional well-being, motivation, and productivity. Facial expressions provide valuable insights into emotional states, and advancements in deep learning and AI enable real-time analysis of facial cues to identify stress indicators. This project utilizes deep learning techniques to develop an automated system for recognizing stress from facial patterns, enabling institutions to provide timely support. By leveraging this technology, institutions can foster a supportive environment, promote emotional well-being, and enhance overall productivity. The potential benefits of this initiative are substantial, and its findings can inform strategies for supporting students and staff.

2 Literature Survey

This system is designed to detect a person's stress level just by analyzing their facial expressions. It works simply using a computer or smartphone's front camera—no extra devices or equipment are needed. It's mainly focused on students and young people, since they tend to spend more time using smart devices, making this technology more accessible for them [**1**].

Stress can often show through small facial changes. In this project, the system focuses on recognizing these changes—especially by tracking how features like the lips and eyebrows move. It uses a method called facial Action Units (AUs), which are small muscle movements that can indicate different emotions or stress levels. The system learns to recognize these using data from two public facial expression datasets (UNBC and BOSPHORUS), and it uses advanced techniques like Support Vector Regression (SVR) to measure the intensity of each facial action[**2**].

The system evaluates facial landmarks and patterns in facial images to determine whether a person is experiencing stress. Its main aim is to provide a real-time, non intrusive method for detecting stress by analyzing facial expressions, with particular attention to movements around the eyes and lips [**3**].

Without saying a word, our face can express a wide range of emotions like happiness, sadness, surprise, anger, and fear. By using emotion detection technology, it's possible to monitor how people are feeling, which helps in identifying stress, anxiety, or even depression. This system aims to support emotional well-being and mental health by detecting emotions in real-time using a webcam [**4**].

Existing System

Current systems for stress detection using facial expressions mainly rely on machine learning and computer vision techniques. These systems typically use a webcam or camera to capture facial images or video and analyze features like eye movement, brow furrowing, lip tension, and other expressions linked to emotional stress.

- Facial Expression Recognition (FER) using machine learning algorithms like Support Vector Machines (SVM) or k-Nearest Neighbors (kNN).

- Using pre-trained deep learning models, such as CNNs (Convolutional Neural Networks), to detect emotional states like happiness, sadness, anger, or fear, which are indirectly used to assess stress levels.
- Some systems are based on Facial Action Coding Systems (FACS), which break down facial movements into action units (AUs) that correspond to specific expressions.
- These models are often trained on public datasets like FER-2013, CK+, AffectNet, or Bosphorus, which contain labeled facial expressions under various emotional states.

3 Proposed Methodology

While current technologies provide helpful tools for managing stress, the proposed system based on facial expression analysis aims to offer a more accurate and targeted. Using Convolutional Neural Networks (CNNs) for analysis offers a non-invasive and more natural way to identify stress. The system applies deep learning techniques to interpret facial expressions in real time by detecting key facial landmarks. These models, trained on diverse datasets, are capable of identifying even subtle signs of stress. To improve detection accuracy, specific features such as eye and facial muscle movements are analyzed. This approach not only enhances the understanding of stress levels but also supports more personalized stress management solutions. By combining image processing with deep learning, the system provides real-time detection, which can be paired with stress-relief activities such as guided exercises, yoga, or customized wellness interventions.

Convolutional Neural Networks (CNNs) are powerful deep learning models widely used in image and video analysis tasks. Their strength lies in preserving spatial hierarchies, allowing them to extract meaningful features from visual inputs effectively. CNNs are trained using large, labeled datasets where each image is categorized into a specific class. Through this training, CNNs learn to identify patterns and visual features that are essential for accurate classification. A typical CNN architecture includes several key layers:

- Input Layer: This receives the image data to be processed.
- Convolutional Layers: These are the core of CNNs, using learnable filters (kernels) to scan the input and extract important features.
- Activation Function: Applied after each convolutional layer, it introduces non-linearity to help the model learn complex patterns.
- Pooling Layers: These reduce the spatial size of the feature maps while retaining important information, helping to make the network more efficient.

3.1 System Design

System architecture serves as the foundational framework for understanding complex systems. By defining components, properties, and relationships, it enables the development of cohesive systems. Architecture description languages play a crucial role in standardizing the representation of system architectures.

Input Acquisition:The system begins by capturing real-time facial images or video streams using a front-facing camera integrated in a computer or smartphone. The input is expected to be a frontal facial view to ensure accurate detection of expressions.

Face Detection:The captured frame is passed to a face detection module. Techniques such as Haar Cascade or Viola-Jones are used to localize the face region, isolating it from the background.

Facial Landmark Detection:Once the face is detected, key facial landmarks (eyes, eyebrows, nose, lips, jawline) are extracted. This step is crucial for identifying Action Units (AUs) that signal emotional stress.

Preprocessing: The extracted facial region is resized, normalized, and converted into a format suitable for input into the Convolutional Neural Network (CNN). This ensures uniformity and improves model accuracy.

Feature Extraction using CNN The preprocessed image is fed into a trained CNN model, which automatically extracts high-level features corresponding to various facial expressions. The CNN is trained on datasets like UNBC and BOSPHORUS to detect subtle stress-related features.

Stress Level Classification:The CNN's output is passed to a classification layer that predicts the emotional category (e.g., Happy, Neutral, Sad). A predefined mapping associates negative emotional states (like sadness or anger) with potential stress indicators.

Result Display:The classified result is shown on the user interface, often visualized in the form of bar charts or status indicators. For institutional use, the result can be stored for future behavioral tracking.

Optional Feedback Module:If stress is detected, the system can optionally trigger stress-relief interventions, such as displaying relaxation techniques, offering guided meditation links, or notifying a counselor or administrator.

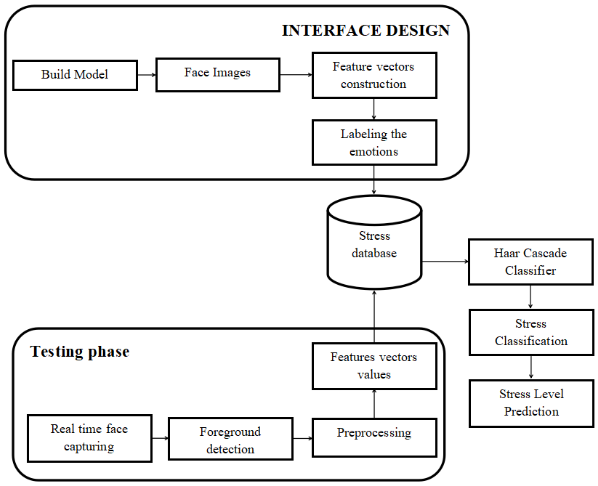

Figure 1: Data Flow Diagram

3.2 Level 0

The Level 0 Data Flow Diagram provides a high-level overview of a system's functional components. It breaks down the system into subprocesses, each handling specific data flows to or from external entities. This diagram also identifies internal data stores and illustrates the flow of data between system components.

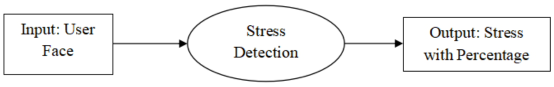

Figure 2: Level 0 Diagram

3.3 Level 1

The next stage involves creating a Level 1 Data Flow Diagram, which highlights the system's primary functions. Typically, this involves identifying 2-7 key processes, depending on the system's complexity. By limiting the number of functions, the model remains manageable and easy to understand.

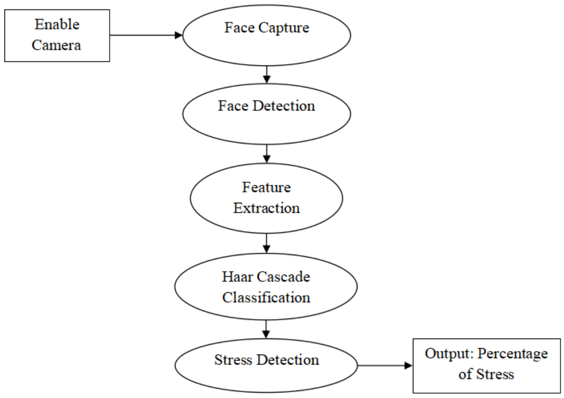

Figure 3: Level 1 Diagram

4 Results

Admin page of the Behaviour Monitoring System to manage user behavior in academic/organizational settings as shown in Figure 4.This is an admin page for a web application named "Behaviour Monitoring System." It's designed to manage and monitor user behavior, possibly in an academic or organizational environment.

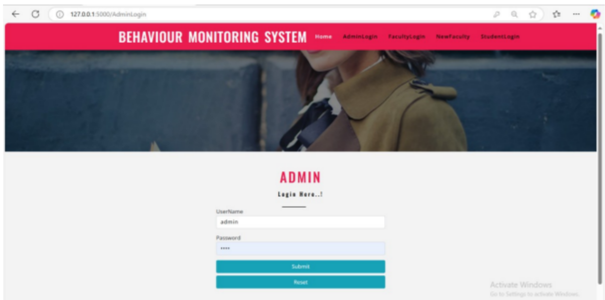

Figure 4: Admin Page

Faculty login page for accessing the faculty dashboard as shown in Fig 5 .This login screen is specifically for faculty members to access their dashboard in the Behaviour Monitoring System, where they can likely view or update behavioral/emotional data of students. It is part of a broader application with different login portals for Admin, Faculty, and Students.

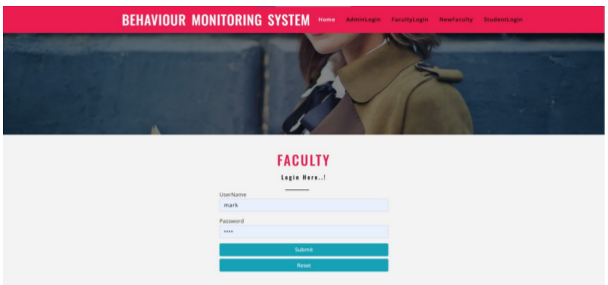

Figure 5: Faculty login page

Student registration form with fields like name, email, batch, etc as shown in Fig 6.This is an student registration page for a Behaviour Monitoring System. It allows users to enter a new student's details such as registration number, name, gender, mobile, email, address, department, batch, and year. The form includes Submit and Reset buttons. The page also has a navigation bar, a footer crediting the designer, and a Windows activation reminder in the corner.

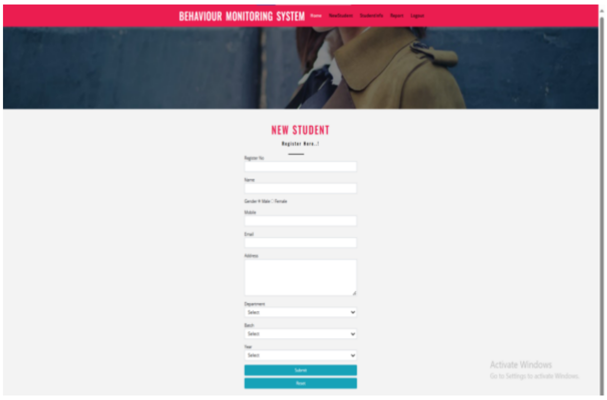

Figure 6: Student registration page

Faculty registration form with name, username, and password fields as shown in Fig 7. This is the New Faculty Registration page of the Behaviour Monitoring System. It allows faculty members to register by entering their Name, Mobile, Email, Username, and Password. The page includes Submit and Reset buttons for form actions.

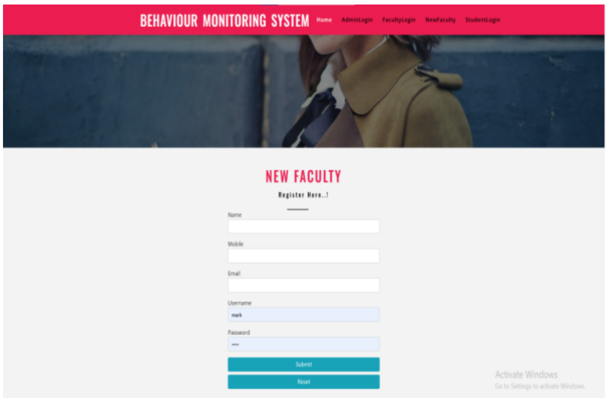

Figure 7: Student registration page

Student login screen with username and password as shown in Fig.8.This is the Student Login page of the Behaviour Monitoring System. It allows students to log in using their Username and Password, with Submit and Reset buttons for form actions.

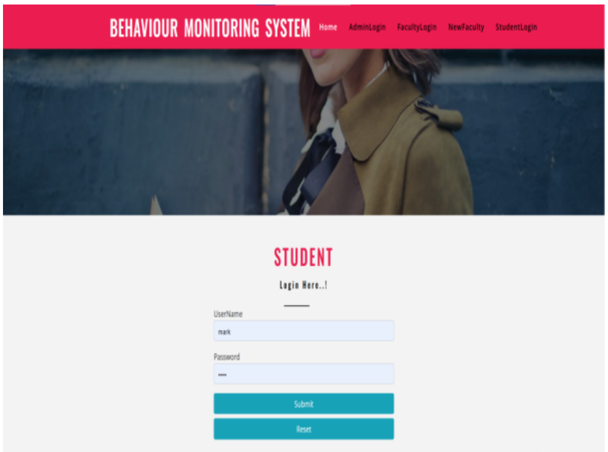

Figure 8: Student login page

Behavior report generation page using Register Number and date range as shown in Fig 9. This is the Behaviour Report page of the Behaviour Monitoring System. It allows users to generate a student's behavior report by entering the Register Number and selecting a date range using "FromDate" and "ToDate" fields. There are Search and Reset buttons to view or clear the input.

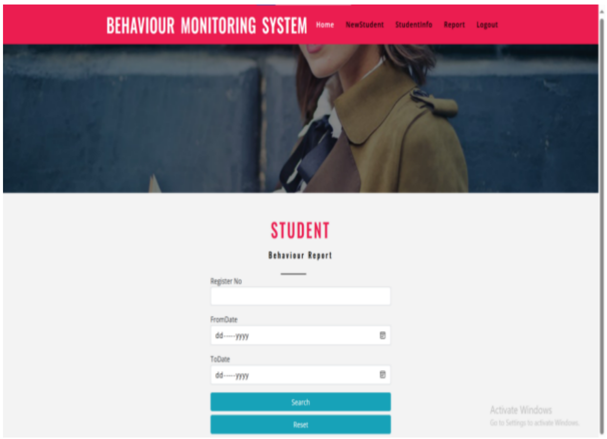

Figure 9: Student login page

Horizontal bar chart comparing emotions: "Sad" (value 20), "Neutral" and "Happy" (value 10 each), indicating "Sad" as most frequent as shown in Fig.10. The image presents a horizontal bar chart comparing three emotional categories: "Sad," "Neutral," and "Happy." Each category is represented by a colored bar, with the length of each bar indicating its corresponding value. The "Sad" category has the longest bar, extending to approximately 20 on the x-axis, suggesting it has the highest frequency or value among the three. Both "Neutral" and "Happy" categories have bars of equal length, each reaching about 10, indicating they share the same value and are significantly lower than "Sad." The distinct colors for each bar help differentiate the categories visually, making it easy to interpret and compare the emotional data at a glance. This chart effectively conveys that the "Sad" sentiment is the most prevalent among the three displayed emotions.

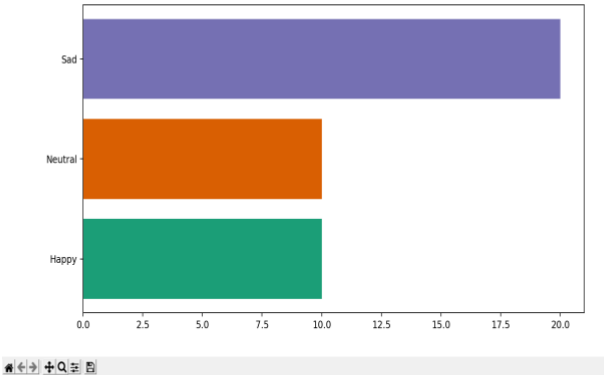

Figure 10: Comparing Emotions

This chart effectively conveys that the "Sad" sentiment is the most prevalent among the three displayed emotions.

5 Conclusion

The proposed facial expression-based stress detection system offers a real-time, non-intrusive way to identify stress levels with improved accuracy. By applying deep learning and image processing techniques, it can detect subtle facial cues associated with stress. This enables the delivery of personalized stress-relief solutions. With its fast and precise evaluations, the system has the potential to promote mental health awareness and support the overall well-being of individuals.

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