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Machine Learning-based Stress Recognition in IT Specialists using Image Processing

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ABSTRACT: Recognising stress in employees is crucial for personal health and improving organisational output, especially in the fast-paced information technology (IT) sector. The demanding workloads, tight deadlines, and high-pressure environments that IT specialists often encounter can significantly elevate stress levels. Prolonged stress negatively impacts mental and physical health and job performance and can lead to anxiety, withdrawal, anger, and ineffective coping mechanisms. Thus, effective methods for identifying and managing stress among IT specialists are essential. A novel approach to detecting and assessing stress levels in IT specialists has been developed, utilising image analysis and ML techniques. This approach aims to address previous limitations in real-time stress detection through continuous evaluation and real-time recognition capabilities. It uses a facial emotion dataset classified into seven emotional states: surprise, happy, anger, sad, disgust, fear, and neutrality. Various ML techniques, comprising convolutional neural networks, random forests, support vector machines, and decision tree classifiers, were trained and evaluated using a validation set. CNNs demonstrated the highest accuracy in predicting emotional states from the training set features. The trained prototype is applied in real-world scenarios, capturing webcam video and uploading images, using Haar cascades to detect faces in each frame, and determining the stress levels of the detected faces. This study highlights the potential for employers to proactively monitor and manage employee stress levels, fostering a healthier and more productive workplace environment that supports sustained professional growth and well-being.

KEYWORDS: Stress detection, Image processing, Machine learning, Live detection, Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Decision Tree Classifiers, Haar cascades.

I. INTRODUCTION

The significance of stress management in preserving unity in society is demonstrated by the Global Healthcare Organisation's acknowledgement of stress as a serious psychological disorder impacting 25% of the population. Conventional techniques for detecting stress depend on subjective self-reporting, which could result in errors. In consequence, the requirement for automated systems that precisely identify stress levels using physiological cues is expanding. Physiological cues used in stress prediction include heart rate, respiration, facial electromyography, and galvanic skin response. A number of technologies and multimodal sensor systems have been created to try and predict stress using pattern recognition algorithms like Bayesian networks and SVM. Some of the issues that persistently continues comprises inter-subject variability in responses and contexts, which are influenced by physiological activity and health conditions, and emotional influence on facial electromyography and galvanic skin response. Another challenge lies in the integration of multiple sensors into robust, accurate, and versatile systems across a diversity of populations and environments. To provide for such functionality, sophisticated algorithms that can analyse, process, and analyse the information from these sensors should be available to identify subtle patterns related to stress events.

Technical and interpretative challenges have reduced the full realisation of the benefits accruable from automated stress assessment systems. Among the popular promising solutions is live detection, which allows real-time monitoring and instant responses to stress. Systematically, this highly improves the management of stress by providing immediate invention, which prevents the kernels of stress from exploding into big problems. This improves individual well-being, productivity, and harmony in workplaces and communities. This shall be one healthy society over some time by reducing stress-related illnesses or improving life quality with the incorporation of live detection systems.

Specialists are facing an unprecedented source of stress in today's fast-paced IT business, which is defined by the constant introduction of cutting-edge technologies and creative products. IT workers are frequently under a great deal of pressure due to the demanding nature of their work, which includes large workloads, tight deadlines, and complex

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projects. Their level of stress is significantly increased by the necessity for ongoing skill upgrades because of the quick speed of technological innovations. Long work hours and a poor work-life balance are now additional problems resulting from a substantial negative influence on the physical and mental health of IT specialists. The impact of stress on an individual's job happiness and productivity is not limited; this additionally includes broader impacts on the performance of organizations. Understanding how vital dealing with these stressors is, this study intends to explore the different aspects of stress that affect IT specialists and offer solutions for creating a more positive and productive work environment. This study addresses the rising stress levels among workers, a problem that continues even in spite of the reality that numerous companies deliver mental health assistance programs. Thus far, initiatives have not led to a solution for the problem. By applying computer vision and ML approaches to assess the structure of stress among working employees, the research seeks to go further into this issue. The study specifically aims to figure out the variables that have a major impact on stress levels. Effective stress level classification is the goal, and methodologies such as CNN classifiers are utilised to achieve this. The employee's image is first captured by an imaging device employing methods for image analysis approaches, which are then utilised as input. By transforming the image into a digital format and performing various operations on it, these techniques improve the image quality and retrieve relevant data.

Inaccurate results in stress detection, which are based on self-reporting, underline the requirement for automated procedures that make use of physiological indicators. While although these systems show great promise, they are not without problems pertaining to individual variability, physical and emotional interference with physiological signals, and the incorporation of heterogeneous sensors. Advanced algorithms are hence in demand for adequate processing and interpretation of these various sensor data to establish patterns of stress with accuracy. This, therefore, is where live detection systems are highly potent to prompt answers for stress and boost the overall well-being of a person, so he or she becomes more productive. In areas like the IT sector, where work load increases and the rate at which technological changes occur is high, specialists experience an incredible amount of stress; it requires proper guidelines for stress management. The purpose of this paper is to comprehend the sources and effects of stress on IT workers and to introduce new solutions alienating image analysis with ML for workspace and workers' health improvement.

II. RELATED WORK

Nikhil Patel, et all. [1] used neural network techniques to manage employee stress, which addressed an issue in human resource management (HRM). By creating, deploying, evaluating, and refining a neural network to categorize workers as stressed or not, they presented an innovative method. Detailed statistical analysis and comparisons with current approaches validated the correctness of their answer offers a realistic solution to HRM problems and provides the way for more research in this field. In their research, they contrasted different employee satisfaction prediction algorithms, such as Naive Bayes (NB), Decision Trees (DT), also SVM. The Employee Satisfaction Index (ESI) dataset was first normalized, and then it was split into cross- validation, model training, also testing sets in a 14:3:3 ratio. The procedure of learning was then validated using kfold cross-validation with k=5. They employed the Logistic activation function in each case embedded and output nodes in their DNN design, which had three embedded layers with a total of seventeen nodes each and an eight-node input layer. The Sigmoid function processed a sequence of weighted sums and biases to calculate the network's output. Nesterov Accelerated Gradient, Adaptive Gradient Algorithm (Adagrad), Adaptive Delta (Adadelta), and Adaptive Moment Estimation (ADAM) were the four optimization methods employed to train the model. The ADAM optimizer produced the best results. The DNN with the highest accuracy (88.40%) and F1 Score (87.28%) was the one that used the ADAM optimizer. Their suggested technique outperformed other classifiers regarding classification rate and F-measure, indicating its effectiveness in stress management for employees.

Naegelin, et all. [2] established and analysed techniques for prescriptive modelling with collected data from several modalities to identify felt stress, arousal, and valence. The dataset, which included 6776 observations from 88 subjects, had 59 attributes derived from physiological (heart rate variability) and behavioral (mouse and keyboard interactions) data. They used SMOTE to reduce class imbalances and reliably standardise these features to account for individual variances. SVM, Random Forest (RF), and LightGBM algorithms were employed in their machine learning pipeline. These algorithms were built using Python packages like scikit-learn and LightGBM. A 10-fold stratified cross-validation approach was utilised in order to maximise the tuning parameters within the models. Evaluation indicators, including weighted average PPV, Sensitivity, F-measure, and AUC, were calculated across low, medium, and high stress levels. Training was conducted on a balanced dataset. The study highlighted LightGBM's improved efficiency and accuracy relative to other algorithms, underlining its superior performance over SVM and RF in detecting stress, arousal, and valence levels.

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Wendy Sanchez, et all. [3] focuses on developing predictive models for desk job stress identification. Using a variety of feature selection techniques, including Analysis of Spearman Correlation, PCA, Correlation-based Feature Selection (CFS), Information Gain, and encapsulation approach for attribute selection, the study collected data from 57 employees in natural settings. The above techniques are applied to managing six datasets: All modalities' features were included in DS01, but features from DS02 to DS06 were chosen or altered using certain techniques. WEKA was utilized to assess the five classification algorithms: J48, AdaBoost (AB), Random Forest (RF), Naive Bayes (NB), k-nearest-neighbor (kNN), ZeroR (ZR), also RF. Standard measures like classification rate, PPV, sensitivity, and F-measure were deployed to assess each algorithm's performance. For a robust evaluation, stratified ten times ten-fold cross-validation was used. As stated by the study, Random Forest outperforms other algorithms such as kNN, Naive Bayes, J48, and AdaBoost regarding classification rate and F-measure, making it the best algorithm for identifying stress in desk jobs. This result, which highlights the validity and consistency of the study's findings, was reached following a comprehensive evaluation utilizing a range of datasets and feature selection methods.

Meshrif Alruily [4] focuses on utilising ML and sentiment analysis approaches to predict worker stress. The study utilizes a composite DNN called HABCABO (Hybrid Artificial Bee Colony with African Buffalo Optimisation), which combines CNN and LSTM. Data from Reddit subreddits regarding mental health contains a range of topics categorised as either stress (1) or no stress (0). Preprocessing was done on the dataset with the aim of getting rid of duplicates, handle missing data, and normalise it for consistency. Employing HABCABO to improve selection and optimisation during feature extraction. Convolution was applied to eliminate features, max pooling was adapted to reduce dimensionality, LSTM was adapted to handle time-series data, and SoftMax was applied to categorise stress states in the CNN-LSTM model structure. Robust features differentiating between long-term and short-term stress levels were found using decision tree approaches; accuracy and reliability in stress prediction were the main metrics for assessment. In general, the CNN-LSTM model that was based on HABCABO had the best accuracy in predicting stress levels.

Sameer Dev Sharma, et al. [5] used a multi-layer neural network according to a DRNN to establish a stress prediction system for working professionals. The objective is to use the Stress Dataset from Kaggle to predict stress more accurately and efficiently. Preparing the data to handle missing values and normalise it, choosing relevant features, and applying advanced algorithms like DRNN, Multi-Layer Perceptron (MLP), and CNN for prediction are the main steps in the process. The study places a significant value on utilising a variety of evaluation standards, including classification rate, sensitivity, selectivity, error metric, and F1-score, to make certain the effectiveness of this approach. The multi-layer neural network based on DRNNs was shown to be the best accurate in predicting anxiety in working professionals among these models. The study emphasises how This strategy is more effective than the alternative methods with regard to prediction accuracy, highlighting its potential to enhance stress prediction in real-world scenarios.

III. METHODOLOGY

The methodology integrates methods for extracting features from images through image processing with ML algorithms to accurately detect stress levels in IT specialists. This multi-step approach ensures a robust and reliable system for stress detection. The block diagram which is depicted in Figure 1 outlines a comprehensive method for detecting stress. It illustrates various phases and modules of the system and the flow of the project.

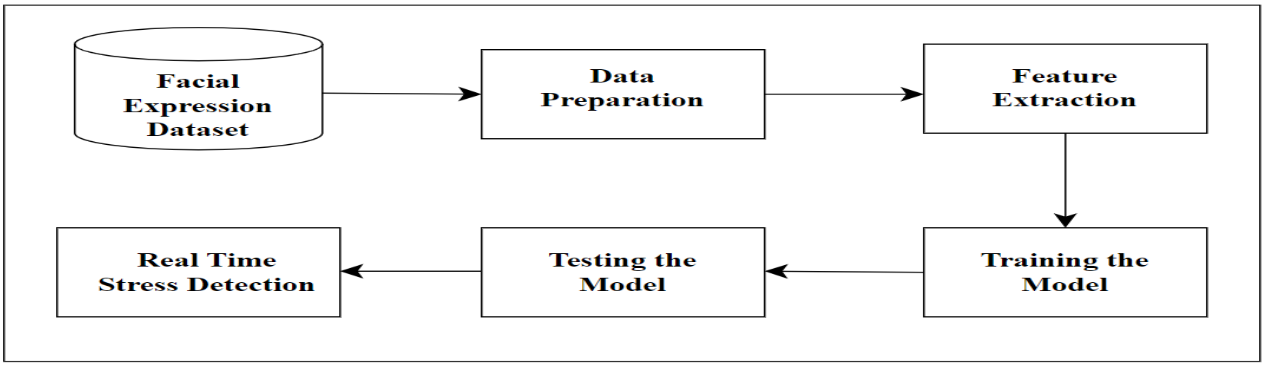

Figure 1. System Block Diagram

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A. Facial Expression Dataset

The dataset contains seven different emotions: anger, neutrality, disgust, fear, happiness, sadness, and surprise. Each image in the dataset represents one of these specific emotions, which becomes very useful for developing models to detect stress in IT specialists. These images include shots of both genders, different ethnicities, and hugely varying age groups. The dataset tries to represent human emotions in all their variations so that most use cases are covered. This dataset is used for further processing.

B. Data Preparation

Data preparation in machine learning involves loading a dataset of images that consists of seven distinct emotions. Each image is associated with a label representing one of these emotions, and the paths to these images, along with their labels, are collected for further processing. Once the dataset is loaded, exploratory data analysis (EDA) is performed. This presents information about the structure and characteristics of the dataset. EDA involves visualising the distribution of the various emotions in the dataset; this is usually done by plots such as bar charts showing how many images belong to each emotion category. This will tell if there is any imbalance in the dataset that needs handling. Overall, data preparation sets the foundation for building effective machine learning models by ensuring the data is correctly loaded, understood, and visually inspected.

C. Feature Extraction

Feature extraction is the process of structuring image data for ML models by converting each picture into a model-comprehensible format. This involves loading the images into grayscale form, converting them into numpy arrays, reshaping them into 48x48 pixels with one colour channel, normalising the images to ensure constant data scales, and label encoding to convert categorical labels into numerical formats. This process speeds up the training process and improves performance by ensuring uniform treatment of all pixel values.

D. Training the Model

Model training is the core process in machine learning, where the goal is to teach a model to make accurate predictions based on input data. This will involve the building and compilation of the model to define its structure and the learning process, followed by matching the model to the data win relation of iteratively adjusting its parameters to improve its performance. The combination of definition, compilation, and iterative learning finally gives the opportunity to come up with a model that can make correct predictions. This is done using a good number of distinctly different machine learning algorithms, which will include SVM, DT classifier, RF, and CNN.

1. Support Vector Machine

In image categorising, support vector machines are the main algorithm for separating and classifying the images into different classes using the features extracted. Unlike the deep learning methods, which automatically discover characteristics from raw pixels, SVMs need some preprocessing steps, where the images are usually changed into grayscale, resized, and then changed into feature vectors. These feature vectors can be regarded as numerical descriptions of an image, characterised by key patterns that most describe one class from another. During training, it finds an optimal separating hyperplane in this space that maximises the margin between two different classes. This hyperplane is sited with support vectors, which are critical samples that lie closest to the decision boundary and influence the classification outcome. In practice, the SVMs support themselves exceptionally well when dealing with small datasets or when the interpretability of results is important, adhering closely to the robust statistical framework for image classification tasks if features are appropriate and well prepared.

2. Decision Tree Classifier

It has a fundamental role in image classification tasks: The classifier separates these images into different classes by utilising the extracted features. Unlike deep learning models, decision trees directly learn from raw pixel data. The basic work includes the examination and partitioning of feature vectors derived from the images. These features are usually flattened representations of pixel intensities or other extracted features used to construct a tree-like structure in which each node represents a decision according to the count of one feature. In this view, according to the decision tree, a series of splits identify boundaries within the feature space that best separate different classes of images. At test time, from the root to the leaf node, each node applies their decision rules and returns the predicted class for a new image after a certain number of steps. This method is intuitive and understandable regarding of insights related to which features are most discriminative for classification. Compared with decision trees, deep learning methods can learn hierarchical representations from pixels, which makes the former relatively bad at enabling complex and high-dimensional patterns.

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3.Random Forest

Random Forest algorithm classifies the images into their respective classes. It does this by creating a form of decision trees, all of which make a estimation derived from different subsets of data. Thus, the final prediction for every image is made by taking a majority vote from all the individual trees. It enhances the general accuracy and robustness of the model due to the reduction of overfitting caused by a single decision tree. Random Forest especially does well with this task because it can treat high-dimensional data, for example, flattened images, working quite well with generalization performance also. With this pre-processed and standardized image data used here, it would quickly and exactly classify new images into those patterns that the Random Forest model learned during the training phase.

4. Convolutional Neural Network

CNNs are basic to any image recognition and classification task because they learn and extract hierarchically complex patterns and features from images in a self-supervised way. They comprise convolution, pooling, and connected layers. Convolutional layers convolve the origin images with certain filters so as to recognise edges or textures, for instance. Pooling layers are applied for reducing spatial dimensions and, hence, simplifying information and diminishing computation in the following step. Classifying images into different categories is typically done by completely interconnected layers at the end of the network, often including activation functions like ReLU to introduce nonlinearity and SoftMax for multi-class problems. CNNs excel in applications involving spatial relationships in data, such as object detection, facial recognition, and medical image analysis, thanks to their capacity for collecting hierarchical patterns and scalability, which has made them a mainstay in modern computer vision applications.

E. Testing the Model

The most important stages during which a ML model is tested for its performance after training. It comprises different steps, of which model evaluation with respect to accuracy and loss is included. The accuracy is the proportion of times that model predictions on the test dataset match actual labels. Loss measures how similar the model's predictions are to real outcomes. The lower the loss value, the better. Additionally, model testing involves making predictions on new or unseen data during model testing and prototyping their performance in the real world. This step incidentally evaluates the model's generalisation capacity over data it has never seen before and, therefore, establishes its practical applicability. Essentially, model testing completes this workflow in ML because of the returned model's efficiency in CCR as well as loss metrics and the validation of its predictions on new data.

F. Real Time Stress Detection

The impulsive best model that came up during training and testing is utilised to build a stress detection system. This encompasses the collect of a video feed from the webcam, which continuously captures frames. Face detection with a pre-trained Haar cascade classifier is utilised to process each frame. Then the frame is converted into greyscale because the face detector works with grey images, and the image size is reduced at each scale of the image. Then, a bounding box would be drawn around the face for each detected face. Extract the ROI in grayscale and further resize it to 48 × 48 pixels, which is the input size expected by the emotion prediction model. Finally, it shows the window with the frame accompanied by bounding boxes and emotion labels.

IV. RESULTS AND DISCUSSION

A stress detection system was successfully developed and tested using a dataset of seven distinct emotions—from anger, neutrality, and disgust to fear, happiness, sadness, and surprise—that could detect the degree of stress in IT specialists. This system is powered by ML techniques and image processing techniques working in several stages. A diversified dataset in many demographics has been successfully loaded and explored. Exploratory data analysis was done to understand how emotions are distributed and if there are any imbalances. Extracted features included turning images into grayscale and resizing them into 48x48 pixels for uniformity. The pixel values have been normalized, and labels encoded, in order to ensure that data is in a format understood by the model.

Multiple ML models, including SVM, Decision Trees (DT), Random Forests (RF), and CNN, were trained. Model performance was evaluated using accuracy and loss metrics, and predictions were conducted on unseen data to validate the model's generalization capability. The CNN model performed well in contrast to the other models, demonstrating high accuracy and low loss, indicating effective learning and prediction. The accuracy graph shown in Figure 2 and loss graph in shown Figure 3. The trained CNN model was then deployed in a real-world application to monitor the stress levels of IT specialists in real time. The deployment process involved several key steps to ensure the system's effectiveness and reliability. First, the system captures video from a webcam, providing real-time footage of the IT specialists as they work, which is essential for dynamic stress level monitoring rather than relying on static images.

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Once the video frames are captured, they undergo a preprocessing stage where each frame is converted to grayscale. Converting to grayscale simplifies the image data, reducing the computational load without significantly losing important information required for facial recognition, which is particularly beneficial for real-time applications where speed is crucial.

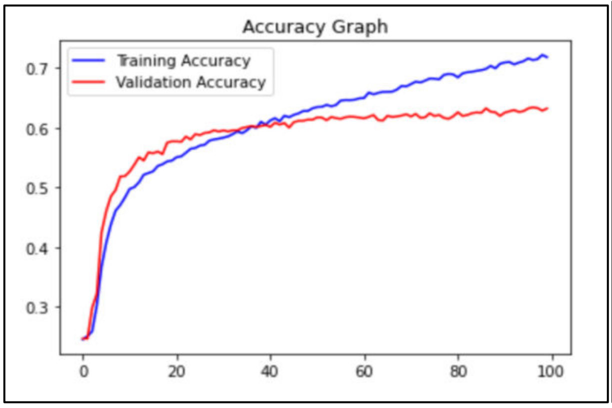

Figure 2. Accuracy Graph

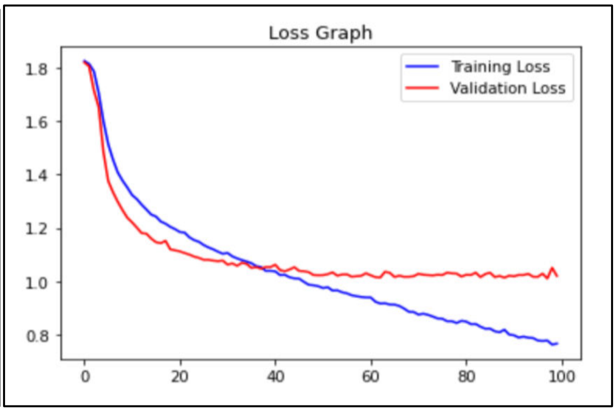

Figure 3. Loss Graph

Next, the system uses the Haar cascade classifier to detect faces within each frame. The Haar cascade is a robust and efficient object detection method that works well for detecting faces even in varied lighting and background conditions. For each detected face, the system draws a bounding box around it, highlighting the ROI. The ROI within the face bounding box is then extracted and resized to 48x48 pixels. Standardizing the size of the ROI ensures consistency in the input data fed to the model, which is essential for maintaining high accuracy in emotion prediction. This resized ROI is passed to the pre-trained CNN model to estimate the stress level of an individual. The CNN model processes the ROI and outputs the predicted emotion, which corresponds to any of the seven categories: happy, surprised, angry, sad, disgusted, fearful, or neutral. This prediction is then displayed on the frame as shown in Figure 4.

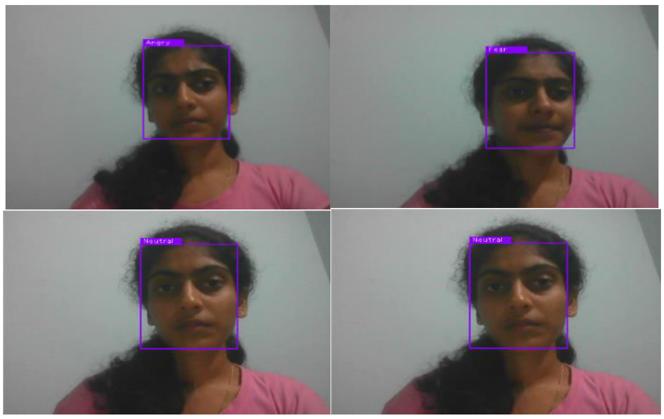

Figure 4. Live Stress Detection

V. CONCLUSION

This study investigated the application of ML and image analysis methods for IT specialists stress detection. Considerable progress has been achieved in understanding and forecasting stress levels through the examination of facial expressions. The results demonstrate how well CNN algorithm categorise stress levels according to the facial data. The study also emphasises how crucial it is to have scalable, non-invasive techniques for measuring stress in work environments. This research enhances occupational health and well-being methods for IT specialists by utilising advances in image analysis and ML. To further improve accuracy and practical applicability, future steps could comprise investigating real-time stress monitoring systems, refining feature extraction techniques, and extending

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datasets. Ultimately, creating proactive support and intervention systems targeted at reducing stress and promoting better work conditions in the IT industry was enabled by the merging of image analysis and ML

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