Predictive Stress Analysis for ITProfessionals: Harnessing Machine Learning For Well-Being

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Abstract*—This paper focuses on developing and evaluating deep learning models for stress detection using Convolutional Neural Networks (CNNs). Stress can be the primary cause of many ailments, such as diabetes, asthma, migraine headaches, and others. Even though there are many remedies for controlling of stress but this issue is way far from avoiding it in humans. Therefore, the model will take into account and use the emotions that are possessed in order to identify stress. The primary objective is to design models capable of accurately classifying input data based on few extracted features from the image data-set collected. Image processing that also include Artificial Intelligence (AI) is used in the beginning that employee's image is taken as the input that includes facial expressions, eye size. By transforming the image into a video and taking into account the expressions in each frame, the useful information is extracted from the picture frame by frame. The corresponding output is then produced. Through thorough capturing of the emotions, our stress detection system demonstrates its effect in accurately identifying stress levels among IT professionals.

Keywords*—Face Expressions, Stress, Deep Learning, CNN.

I. INTRODUCTION

Stress have been a significant issue of the general public all over the world. Nowadays because IT industries are measuring a lot in moving the society further and bring up new technologies, the stress levels in employees who use computers are also observed to raise. We start by using image processing to capture the working facial expressions of IT professionals in order to accomplish our stress detection system goals. The images are analyzed and then converted into video. We take out pertinent data that represents their emotional condition. The system categorizes these expressions, such as smiles, dizziness or raised eyebrows, to generate appropriate outputs corresponding to their emotional signs only if the employee is in front of the camera. The extracted facial expressions are then given as input to the Deep Learning model, which undergoes a training process to optimize its performance. By making efforts and analyzing the emotional expressions, our stress detection system signifies its effectiveness in accurately identifying stress levels among IT professionals. This capability makes it a valuable tool for addressing stress related challenges, allowing early involvement in identifying and support for individuals experiencing more intense stress. Our stress detection system's user-friendly design is easily transferable to real-world IT environments. Its nature of not causing someone to feel uncomfortable and smooth implementation provide necessary support to IT professionals, empowering them to manage their stress effectively. By recognizing and addressing stress instantly, the system contributes to a healthier and more productive work environment. In the succeeding part of this paper, we go through the detailed methodology, including the image processing techniques, challenges encountered, and the outcomes achieved. We will delve into the technical details of feature extraction, data preprocessing, model architecture, and training procedure for CNN model, and data collection procedures. In addition, we present the evaluation results, displaying the accuracy and efficiency of the stress detection model we developed in real world scenarios. Continuous capturing of images even if the employee is not in front of the camera leads to more data storage of the images that are not required. Eventually, we believe that the successful implementation of this innovative stress detection system will play an important part in increasing the overall protection and performance of IT professionals. By providing sustainable support and understanding the stress levels, the system can positively impact not only individual employees but also organizational productivity and gives job satisfaction.The project's dataset consists of previously acquired photos. Definitely the accuracy differs from the earlier projects as the methodologies and implementation is varied. Here in this project, we will be modelling Deep Learning models i.e; Convolutional Neural Networks (CNNs).In this project, we will be calculating accuracy and we will also give an output whether the image is stressed or not.

II. RELATED WORK

Numerous approaches have already been put forth and published in various journals. Each of the papers discussed in this section takes a distinct tack on the problem. Below is a discussion of some of the current techniques:

[1]The primary goal of this project is to utilize Machine Learning and Image processing techniques in order to identify stress in individuals through their facial expressions. The model is an improved stress detection system that encompasses live monitoring of employees, physical and psychological stress tests and provision of relief by giving a warning. The main focus is on creating a healthy work environment for employees. The system captures images of employee's facial expressions and processes them to detect stress indicators like anger, sadness, and more. Machine Learning (ML), particularly K-Nearest Neighbor (KNN) Classifier, is utilized to categorize stress levels based on the captured expressions from the images.

[2]The implementation of the project involves several modules. The User module allows employees to register and provide images as input. The admin module activates users and can view the results of stress detection. Data preprocess module

performs feature extraction using Principal Component Analysis from the input dataset. haarcascade_frontalface_default.XML classifier for image processing. The architecture is designed to handle real-time stress detection, making it possible to monitor stress levels of employees regularly and take active measures for stress management. Overall, the system introduces a new approach to stress detection using ML techniques, particularly KNN classifiers. At the initial stage of detection, the system employs the Image Processing techniques based on the image of the employee (taken by the system). This entails digitizing the picture and processing necessary procedures for deriving useful details. The stress recognition subsystem is targeted at identifying facial expressions like anger and sadness that may denote a stressful situation or condition.

[3]This project's focus is on the IT industry, which is introducing new technology and products to set new standards in the market. However, the IT industry is also facing challenges related to employee stress levels. Despite many companies providing mental health benefits, stress-related issues remain a concern. This project aims to delve deeper into the topic of stress patterns in working employees within businesses.The project utilizes image processing and machine learning to identify stress patterns and focus on the key variables causing high-stress. The system will employ machine learning tactics like KNN classifiers for classification of stress levels by considering the details retrieved from pictures.

[4] Using wearable technology, this study examines mental stress levels by measuring physiological signals such as ECG, skin conductance, respiration, and EMG. In total, 19 measures were recorded from these measures.After carefully analyzing the correlations and normalized feature values, we chose a subset of 9 features out of the original 19 for our subsequent research. To further refine our data, we applied principal component analysis and reduced the number of attributes to 7.By using such characteristics and various classifiers which includes the Fisher's Least Square Linear classifier, the KNN classifier, the Quadratic Bayes Normal Classifier and the Linear Bayes Normal Classifier, they reached an accuracy rate of about eighty percent between the employees. The experiment is very close to what Philip Schmidt did in terms of the count of participants involved and qualities extracted. Their report used three different stressors in comparison to other stress classification papers that utilized one type of stressor.

[5]The SWELL Knowledge Work (SWELL KW) dataset was created as a result of this project, providing researchers with a new multimodal resource for studying stress and user behaviour. The data was collected from 25 participants carrying out common knowledge activities such as reading, writing, browsing amidst others in the process controlled working conditions with two stress features namely email interruption and time pressures. These recorded data also has body postures/facial expression/computer logging/skin conductance and heartbeat. All the employees were given with this dataset of raw and pre-processed data with features that are extracted. Validated questionnaire for task load, mental work and so forth were used to regulate the dataset on working behavior and affect.

[6]In this fascinating study, researchers delved into the intricate details of measuring stress, using various methods such as heart rate, EMG, GSR, and breathing data. Interestingly, they discovered that respiration played a significant role in determining stress levels. To predict stress, the researchers even applied ECG signals and used sophisticated techniques like the J48 algorithm, SMO, and Bayesian Network algorithm on data gathered from 16 participants experiencing four different types of stress scenarios.

[7]This paper's main value lies in creating a new te-sting method to effectively trigger various degrees of stress. It also brings a new system using EEG data to spot different stress levels. The system identified stress with peak accuracy of 94.6% comparing two stress levels and the control and 83.43% between stress and other stress levels. The findings imply EEG signals might be a stable way to recognize stress levels.

[8]Around 70% of US citizens face stress, potentially causing lasting health problems such as cancer, heart diseases, sadness, and diabetes. To identify stress, researchers used advanced neural networks, specifically a 1-D waveform neural network and a multi-layered brainlike network. These systems pull out key points from base data, studying body signals from sensors worn on the- chest and wrist.The smart network we call a deep convolutional neural network got a score of nearly perfect. It got 99.80% and 99.55% for seeing stress in two tests. Also, it scored 99.65% and 98.38% for figuring out emotions. We used two different types of smart networks for these tests - one was a 1D convolutional, and the other was a multilayer perceptron. Both tried to detect stress and emotion from body signals. We got these signals from devices attached to the chest and wrist. Compared to oldfashioned ways, these networks performed much better. In fact, it shows the power of smart networks for creating methods that are strong, go on all the time, and don't bother the person wearing them for detecting stress and figuring out

emotions. This can help make life better for people.

[9]This project unveiled the WESAD dataset for the objective of detecting stress and emotions using wearabletech, and it is now accessible to everyone. To gather this data, 15 individuals were selected. Devices like RespiBAN Professional and Empatica E4, worn on the chest and wrist, captured a variety of physiological information. These included three-axis acceleration, electrocardiogram, blood volume pulse, body temperature, respiration rate, electromyogram and e-lectrodermal activity readings.The properties were tested under different conditions like normal, happy, tense, relaxed and so on. They utilized and evaluated five computer-based methods for identifying tense states. These me-thods include KNN, Linear Discriminant Analysis (LDA), Random Forest (RF), Decision Tree (DT), and AdaBoost (AB). With typical features and traditional machine-based approaches, they were able to correctly categorize up to 80.34% and 93.12% for the three-way (happy vs normal vs tense) and two-way (stress vs no stress) classifications, respectively.

[10]Through the use of cutting-edge machine learning, this project delved into the complex realm of workforce stress patterns and identified the most significant factors that contribute to its manifestation. Thorough data cleansing and rigorous preparation paved the way for a comprehensive analysis using a variety of machine learning techniques. The resulting models were carefully evaluated and compared, with boosting emerging as the most accurate. Notably, decision trees highlighted crucial characteristics such as gender, family life, and access to health benefits as key influences on stress levels. With this valuable knowledge at their disposal, businesses can now proactively address stress and foster a more positive working environment for their employees.

III. METHODOLOGY

In our model, we focused on stress detection using image data as our primary source. To enhance the dataset's quality and diversity, we employed various preprocessing and augmentation techniques. Initially, we gathered image data from the internet. Our proposed system utilizes facial emotion analysis to determine that if a person is experiencing stress or relaxed. Here, we use trained data to assess and ascertain whether or not a person is under stress. Image processing is used to enhance the image and extract pertinent data. By considering input as a measure and obtaining output that indicates whether or not the person is stressed.

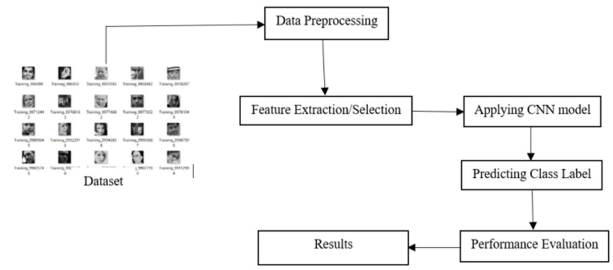

Fig.1. Architecture of proposed model

A. Data set

We have collected the dataset for our problem statement from the internet. This dataset is split into test and train directories that are both further divided into stress and no stress folders, this stress and no stress are two classes.

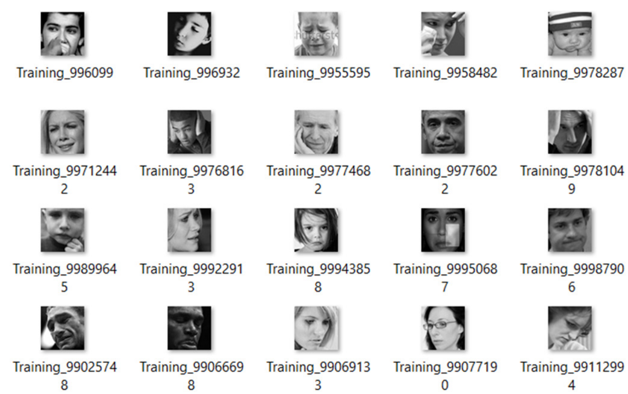

Fig.2. Image Dataset

A. IMPLEMENTATION

i. CREATING A NEW MODEL:

Firstly, we initialize a pre-trained MobileNet model for image processing, configured for an input shape of 224x224 pixels with three colors, they are Red, Green, Blue(RGB). Subsequently, it fixes the weights that are allocated to all layers in the MobileNet model, ensuring that the pre-existing knowledge is retained and not modified during the upcoming training phase.We then place a custom sorting top on the model. It's made up of a layer that smooths things out, followed by a chunky layer with seven parts. This chunky layer uses a SoftMax trigger tool, which shows it's suited for a task that divides things into many different groups. Finally,the model gets built with the Adam optimizer. It uses categorical cross-entropy for the loss function, and accuracy is the way it's evaluated. This compilation step prepares the model for training, making it ready to learn and make predictions on a dataset with seven output classes.

ii. DATA PREPROCESSING:

This sets up image data creators for training and confirmation using the Keras 'ImageDataGenerator' class. When preparing the teaching data, some methods were added like zooming, tilting, and switching the image's side. This makes the dataset more varied and helps the model understand better.Furthermore, the pixel values are transformed to fall within the range of 0 to 1, resulting in better readability and visual representation.To ensure that our images are of the correct size (224x224 pixels), have the desired batch size of 32, and are properly located within the directory, the target path is also specified.

The class indices of the training data are extracted, providing a mapping between the class labels and their corresponding numerical indices. In the validation dataset, we solely rescale the data without implementing any augmentation techniques. We utilize a 'flow_from_directory' approach similar to that used for generating batches in order to evaluate the model. This comprehensive code establishes a dependable data pipeline designed to train and validate a neural network model on a stress detection dataset with a designated directory composition.

iii. MODEL IMPLEMENTATION:

A. Loading the best fit model:

In this instance, the Keras library is harnessed to load a pre-trained neural network that has been saved in the HDF5 file format (".h5"). With the use of Keras' load_model function, the model is effortlessly loaded from the designated file location. It allows the user to retrieve a previously trained and saved neural network, providing the opportunity to use the model for various tasks, such as making predictions on new data or fine-tuning for specific applications. It is important to check the architecture and configuration of the loaded model match the expectations, especially if the model is intended for deployment or further training.

B. Training and Testing the model:

Demonstrating the impressive display of creating and training a basic neural network utilizing keras on manufactured data. Initially, synthetic data consisting of 1000 samples with two features is generated, and binary labels are assigned based on a condition. The Sequential model is created, consisting of three densely connected layers. The first two layers utilize ReLU (Rectified Linear Unit) activation,the ultimate layer employs a sigmoid activation function for the purpose of binary classification. The model is put together using the Adam optimizer, incorporating a learning rate of 0.001. The selected loss function is binary cross-entropy, while the model's performance will be judged based on its accuracy.

To enhance the model's generalization capabilities, a data augmentation generator is employed through the 'ImageDataGenerator' class. This generator introduces variations in the training data, including rotations, shifts, shearing, zooming, and horizontal flipping. The fit method was used to train the model on synthetic data, with the epochs, batch size, and 20% validation split being specified. The metrics for evaluation were set to accuracy. Training was carried out for 50 epochs with a batch size of 32 and a validation split of 20% to ensure reliable results.

The accuracy and validation accuracy over the epochs is skillfully captured through Matplotlib's visualizations, providing a valuable glimpse into the training progress. The dynamic display of the models performance on both the training and validation datasetall over the training period showcases its impressive capabilities.

Training Information:

The model underwent rigorous training over 50 epochs, with each batch containing 32 samples. Throughout the training process, we utilized the highly efficient Adam optimizer with a learning rate set at 0.001 and a split of 20% of the data for validation. To accurately assess the model's progress and success, we employed detailed plots to keep a close eye on the training and validation accuracy, and also the loss function.

Testing Information:

OpenCV is used to implement the model, which will identify real-time stress values from the device's webcam video storage. Each and every frame of the live video stream is captured using OpenCV's VideoCapture feature. The software recognizes the face and eyebrows once every second. The captured images will be compared with the dataset images and if they are matched then output will be displayed as stress and if it is not matched, then the output will be the No stress.

C. Deploying the Model:

Using Tkinter framework, we are designing a GUI. In this graphical user interface (GUI) with features for user authentication, live video streaming, and real-time stress detection. It incorporates a pre-trained neural network model (NN) for stress prediction and a cascade classifier for face detection. The Tkinter framework is used to create the GUI, including a login screen with username and password entry, a main window with a video display, and buttons for starting and stopping the video feed. Stress detection is visually indicated on the video stream by rectangles around detected faces, and a buzzer sound is played when stress is detected. The application provides a practical example of integrating computer vision, machine learning, and user interface components to create a stress detection model.

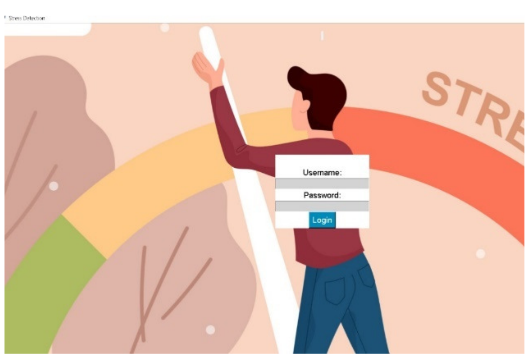

Fig.3. User Interface

IV. RESULT ANALYSIS

CNN:
Our project utilized a state-of-the-art CNN with a remarkable accuracy rating of 98.75%. The image capturing and the output showed precision of 99.80%, recall of 99.71%, and F1-score of 99.75%, which displayed that stress versus non-stress.

	Accuracy	**Precision**	**Recall**	**F1-Score**
CNN	0.9875	0.9980	0.9971	0.9975

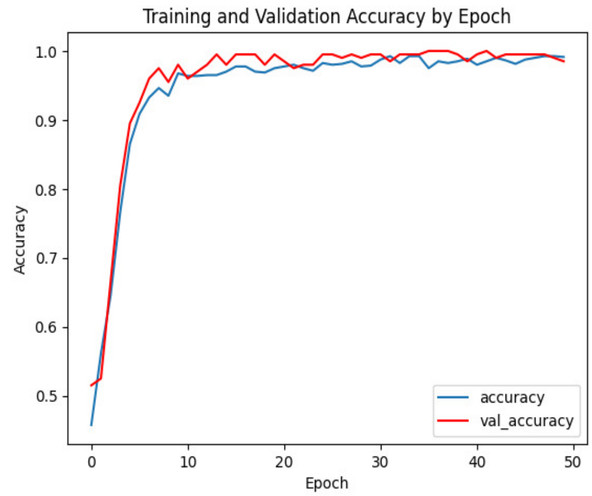

Fig.4. Training and Validation Accuracy by Epoch

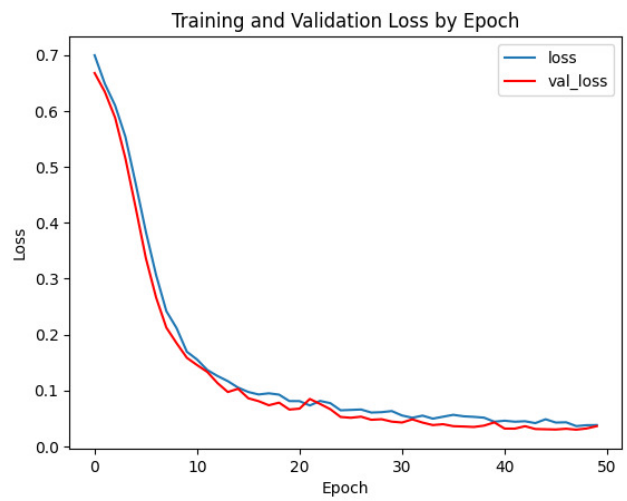

Fig.5. Training and Validation Loss by Epoch

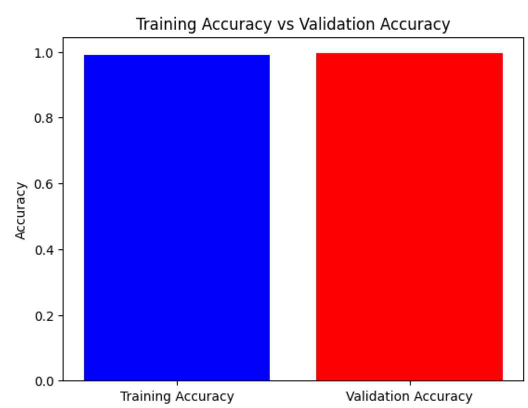

Fig.6. Training Accuracy vs Validation Accuracy

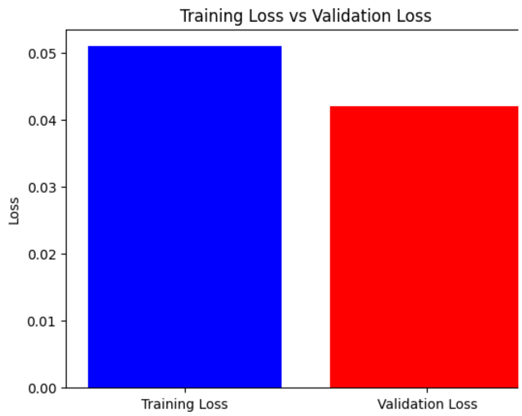

Fig.7. Training Loss vs Validation Loss

While testing the model, the User interface is opened and after entering the credentials, the camera starts capturing images and the captured images are compared with the dataset images and if matched it displays 'Stress Detected' and a buzzer sound is played.

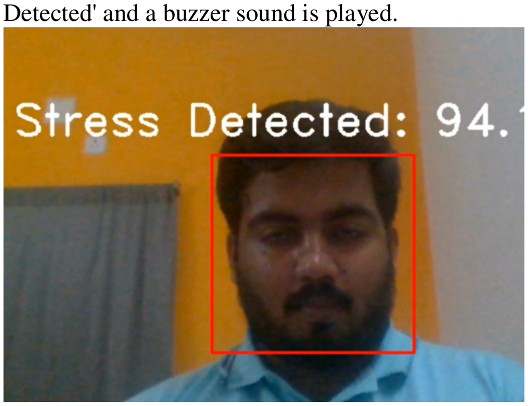

Fig.8. Stress Detected

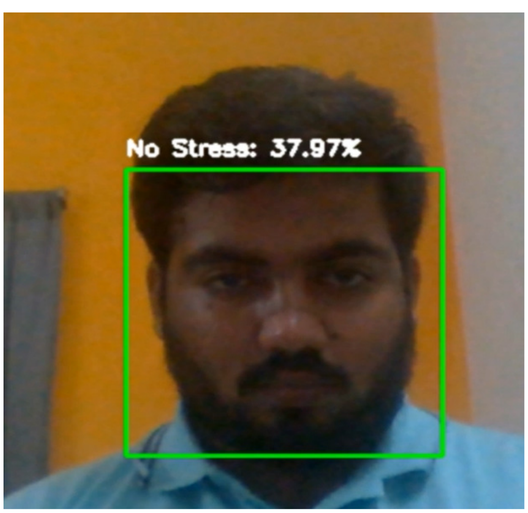

Fig.9. No Stress Detected

V. CONCLUSION

Convolutional neural networks (CNNs) are used in this project, to produce results that are both efficient and effective in comparison to other systems. We have successfully classified 2 different classes such as 'stress' and 'no stress' from the samples of the dataset by constructing a sequential 7- layer CNN model, which has a good accuracy of 98% to detect the stress of the IT Employees. Assist organizations in monitoring the stress of their employees and implementing appropriate measures to enhance their well-being and performance. The stress detection system aims to assist IT Employees in determining whether they are experiencing stress or not. The project can also be further developed by identifying stress as it identifies all the emotions of many people within a single frame as it identifies these emotional responses in real-time video recordings.

Finally, our future studies will focus on incorporating the audio stream in the framework and investigating audio-video approach towards stress recognition accompanied by advice to cope with a distressed state. Additionally, we have intentions of incorporating different algorithms other than CNN and see how accurate it becomes after evaluating the results obtained from different algorithmic approaches.

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