# Stress Detection Using Deep Learning Algorithms

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***Abstract*—Stress has become a prevalent issue in modern society, with various negative impacts on mental and physical health. Stress in people is a physiological and psychological reaction to an imagined threat or difficulty. Several things, including employment, relationships, income, health problems, and significant life transitions, can cause stress. Depending on the person and the circumstance, stress symptoms can vary. They frequently include emotions of worry, irritation, and restlessness, as well as physical symptoms like headaches and muscle strain. Early stress detection is crucial for effective intervention and prevention of stress-related health issues. Detecting stress in real-time can be valuable in various domains such as healthcare, mental health, human-computer interaction, and workplace performance. This paper proposes a method for detecting stress using deep learning. A set of pre-trained models are employed for stress detection. The proposed technique is evaluated with publicly available datasets. Experimented results showed that the proposed stress detection method achieves accuracy in the range of 85.71-97.50% and the loss ranging from 0.4061 to 1.8144.**

***Index Terms*—Depression; Stress and Its Symptoms; Stress Detection; Medical Imaging; Deep Learning; Accuracy.**

## I. Introduction

Stress is a natural response of the human body to external or internal pressures perceived as challenging or threatening. It is an aspect of the body's survival mechanism that enables fast reactions to potential threats [1]. Everyone experiences stress occasionally, and several things can bring it on, including work, relationships, financial strains, and health issues. Yet, persistent or severe stress can harm physical and mental health, resulting in disorders like anxiety, depression, and cardiovascular diseases [2], [3]. To assist people in managing and preventing linked problems, stress detection can be employed in various situations, including healthcare, sports, and the workplace.

The technique of identifying and assessing the physiological or behavioural changes that occur while a person is under stress is known as stress detection [4], [5]. These changes may include increased heart rate, blood pressure, shallow breathing, perspiration, and muscle tension [6]. Stress detection is crucial for individuals and businesses to recognize stress and respond appropriately. Self-reporting, physiological measurements (such as heart rate variability, cortisol levels, and skin conductance), and behavioural measures are some techniques used to identify stress (such as changes in speech patterns, facial expressions, and body language).

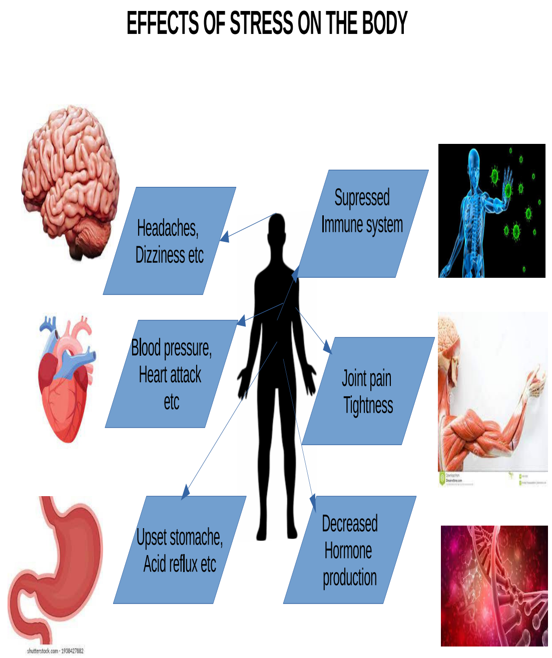


Fig. 1: Impact of Stress on Health

The impacts of stress can be felt throughout the body, but especially in mind, which can cause unanticipated changes in behaviour. It is best to manage stress by being aware of its common symptoms. Alternatively, unmanaged stress can result in various health problems [1], [7]. For instance, this continuous stress may increase the risk of high blood pressure, a heart attack, or a stroke [8]. Figure 1 shows the effects of stress on health. People in a few countries experience high-stress levels due to the recent economic suffering brought on by COVID-19 [1], [9]. It is hardly shocking that stress levels are still very high. In addition, the United States is one of the ten most stressful nations on earth, with a high suicide rate. Figure 2 gives the world's most stressful countries.

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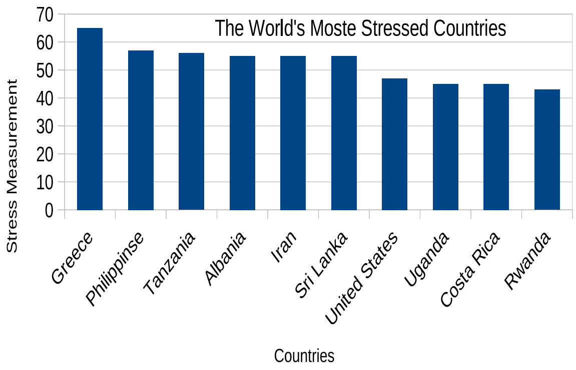



Fig. 2: The World's Most Stressed Countries [10]

Millions of individuals throughout the world struggle with stress, which is a widespread issue. Early identification is essential to preventing negative results, as stress can majorly affect a person's physical and mental health [11], [12]. Deep learning algorithms have demonstrated considerable promise in recent years for detecting pressure from physiological signals. In this paper, we propose a deep learning-based method for stress detection. A few standard CNN models are employed and evaluated under the proposed method. Multiple well-known performance metrics such as accuracy, precision, recall, and F1-score are evaluated to see the effectiveness of our proposed scheme. Experimented results showed that the proposed stress detection method achieves accuracy in the range of 85.71-97.50%.

The rest of the paper is organized as follows. Section II provides related works. Section III describes the proposed work. Section IV analyzes experimental results. Section V concludes the paper.

## II. Related Works

Previous works on stress measurement focused on collecting and analyzing physiological data and then identifying the correlation between perceived stress and multiple physiological features. Recently researchers have focused on detecting stress using machine learning algorithms [1], [4], [13] and methods across various fields, including psychology, neuroscience, computer science, and engineering [14], [15].

Ayten *et al.* [14] used wearable medical sensors (WMSs) to capture physiological signals. The authors included five parameters: electrocardiogram (ECG), blood pressure monitor, galvanic skin response (GSR), respiration monitor, and blood oximeter. Utilizing the k-nearest neighbour (kNN) algorithm, their approach got 95.8% accuracy in stress detection. Enrique *et al.* [16] exploited the potential of mobile phones as stress detectors in working environments. They gathered information from an environment with no restrictions and unknown stressors. They used accelerometer data to characterize by removing time-domain and frequency-domain information from the participants' behaviour. Rajdeep *et al.* [17] has given an Overview of the suggested technique for identifying stress from four physiological signals like interbeat interval, electrodermal activity, skin temperature, and blood volume pulse. Samarasekara *et al.* [15] tried to detect stress using speech and facial expression recognition. The Ryerson audio-visual database of emotional speech and song (RAVDESS) and the Berlin database of emotional speech (EmoDB) were analyzed to detect stress, and they got 80% accuracy. Priyadarsini *et al.* [18] tried to see stress during playing games. The fast Fourier transform (FFT) approach was used to acquire power spectral densities following the normalization of the processed EEG signals. They obtained accuracies of 78% to 90%. Dae *et al.* [19] created a wearable glove device to quickly identify stressful driving situations. The driver's hand movement pattern assesses the steering wheel motion. By employing a traditional CNN architecture Alex-Net, Bikramjit *et al.* [20] proposed a model for analysing distress in people through their facial expressions. They achieved training and validation accuracies up to 93.4% and 92.5 %, respectively. Wonju *et al.* [21] demonstrated a deep learning-based stress detection technique that combines physiological data with the sequence of face attributes collected from facial photos. Aurobinda *et al.* [16] offered the use of facial patches as a technique for identifying facial expressions of emotion. The recommended system performed with an average F-score of 92.22 %, 91.8 % recall, and 92.63 % precision. Ding *et al.* [22] emphasized a method for identifying depressed people through the rise of social networks. Melo *et al.* [23] used deep learning methods for depression detection by exercising 2D convolutional neural networks (CNNs). Amogh *et al.* [24] used IoT and deep learning methods to recognize stress. They used textual data and facial expressions to identify stress. They received training and validation accuracies up to 79% and 77%, respectively. Eren *et al.* [23] gave a method to detect stress with Deep Learning using electrodermal activity and blood volume pulse signals. The suggested model produced an accuracy of 96.26%.

Other stress detection techniques and instruments have been developed due to recent technological breakthroughs—for example, Anusha *et al.* [25] recorded Physiological data using a standalone battery-powered wrist wearable from Analog Devices. The device, also known as Analog vital signs monitoring (ADI-VSM), is a wristwatch-style device that allows for continuous monitoring of electrothermal activity. They observed the test dataset's accuracy up to 97.83%. Another development includes mobile apps that use self-reported data to identify stress levels and automated systems that analyze speech and facial expressions to identify stress are a few examples. Smartwatches and fitness trackers are wearable devices that record heart rate variability and skin conductance. These technologies track physiological and behavioural reactions to stressors using a variety of sensors and algorithms and then provide tailored recommendations for stress reduction methods. In addition to helping people better understand and manage their stress levels, stress detection can potentially improve the diagnosis and treatment of stress-related diseases [2], [26]. However,

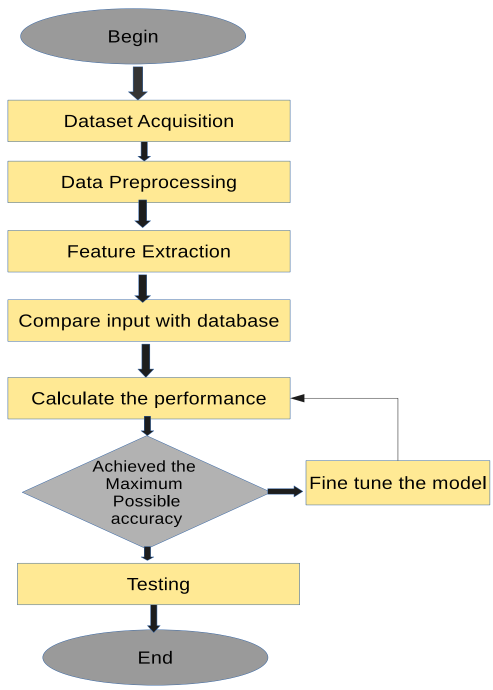
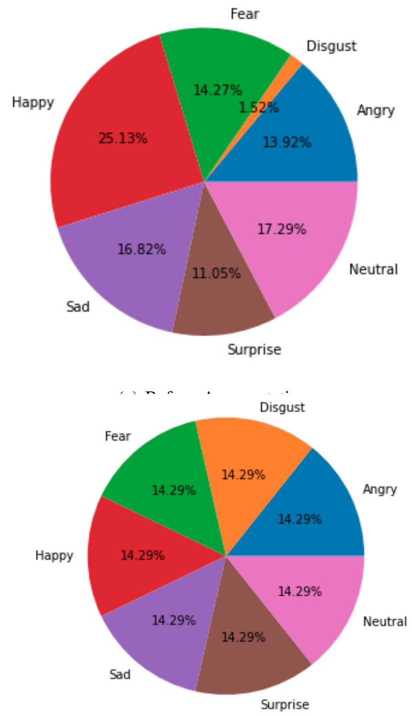



Fig. 3: Schematic flow diagram of Stress detection methodology




(b) After Augmentation

Fig. 4: Dataset Visualization

the precision and dependability of stress detection techniques and the possibility of sensitive data exploitation remain issues. Thus, it is crucial for researchers and practitioners to continue developing and evaluating stress detection methods and to address ethical considerations related to their use.

## III. Proposed Work

Deep learning has transformed the field of artificial intelligence and has been applied to tackle various challenging issues in healthcare sectors. For example, Deep learning techniques can help spread the complex problem of stress detection. Here we suggest a customized deep-learning model for detecting people's stress. The proposed Deep learning model is a multiple-layered artificial neural network. The neural network works in stages to notice stress. Figure 3 shows a schematic of the series of steps of the proposed stress detection methodology.

### A. Data Acquisition

Data acquisition in AI technology, e.g., machine learning and deep learning, is one of the most critical steps. The data acquisition phase in the proposed system is responsible for collecting data, e.g., images, audio, etc., from the public or local environments. This phase contains image datasets on human emotions to see how the proposed model performs on a new dataset being trained on the prior collected dataset. The collected images may initially be in different dimensions. The data acquisition phase transforms the input dataset into a desired format of a learning algorithm used for training purposes. Once the training phase is over, i.e., acquiring some training data, the proposed model learns to predict standard performance metrics for a new task( here, stress detection). Our work exploits a large dataset sample to train the selected deep-learning models to learn accurately and effectively.

### B. Data Augmentation

Data preprocessing is a crucial stage in the machine learning pipeline since it dramatically impacts the model's performance and accuracy. While improper data preprocessing can provide biased or erroneous findings, proper preprocessing can increase the model's accuracy. The collected dataset may include low-resolution photos, some of which could be challenging to identify or correctly categorize. Also, the dataset consists of a sizable percentage of neutral faces, which could impact how healthy emotion detection models function. The performance of the models can be increased thus by using preprocessing techniques like data augmentation and balancing. The collected data in this work are balanced using the synthetic minority over-sampling technique(SMOTE) approach. SMOTE is a method often used in data mining and machine learning to solve the issue of class imbalance. In addition to resolving a class imbalance issue, our approach can predict the minority class of emotions. Figure 4 shows the dataset collected for different emotion states before and after augmentation.

### C. Model Selection

The correct architecture and hyperparameters for the neural network must be selected as part of the deep learning model selection process for adequate stress detection. The performance and generalizability of the model can be considerably impacted by the model selection, making it a vital step in deep learning. This work considers four deep learning models—EfficientnetB0, Fernet, VGG16, and Resnet50 because of their high performance.

- **EfficientNetB0:** EfficientNet-B0 is a convolutional neural network (CNN) architecture belonging to the EfficientNet model family. An EfficientNetB0 model demonstrates outstanding performance in several computer vision tasks. The effectiveness of EfficientNetB0 in stress detection can be related to its capacity to recognize intricate features and patterns in the input data and its deep design and effective utilization of CPU resources.
- **Fernet**: Another deep neural network architecture utilized for stress detection is Fernet. One of Fernet's advantages is its simplicity, making it simple to deploy and train. Fernet leverages the power of CNNs to automatically learn relevant features from facial expressions and classify them into stress or non-stress categories.
- **VGG16**: A well-known deep neural network architecture called VGG16 is applied to numerous computer vision problems. VGG16, also known as the Visual Geometry Group 16, is a famous convolutional neural network architecture for image classification. We employ it here to its ranging promising results in stress detection. The success of VGG16 can be due to the deep architecture, usage of small convolutional filters, and capacity to capture fine-grained features in the input data.
- **ResNet50**: Another well-liked deep neural network design used here for stress detection is ResNet50. ResNet-50 has been widely used for object detection, image classification and segmentation, etc. ResNet-50 is part of the ResNet family of models, known for their deep architectures with skip connections that address the vanishing gradient problem, allowing for the training of deep neural networks. The success of ResNet50 can be ascribed to its ability to use skip connections in its architecture to address the issue of vanishing gradients.

Each image of size $48 \times 48$ of greyscale is given as input in these models. The number of samples, known as batch size, will be processed by each model simultaneously during training which is also kept to 64. The learning rate used by the Adam optimizer during training is 0.0001. Every model is run up to 100 epochs. However, a model may reach the expected results before 100 epochs. The collected dataset is divided into 80:20 ratios for training and testing purposes.

### D. Feature Extraction

Feature extraction is another essential part of the proposed customized deep learning approach. In this stage, the initial image dataset on human emotions is divided and dimensionally reduced to more manageable groups. In other words, the feature extraction phase in the current scheme determines the best features from the input datasets. In this work, we exercise a large dataset that needs more computing resources. Therefore the extraction phase in our approach is functional and reduces computing resource size. Consequently, this phase reviews redundant data from the given dataset without losing relevant information. Therefore the learning speed of the proposed model increases.

## IV. Experimental Results

The proposed approach is evaluated for four deep learning models mentioned above. They are assessed for standard performance metrics and improved to produce reliable results. After 20 training epochs, it is seen that the models delivered promising results, with the training process using 80% of the available data.

### A. Dataset Preparation

A publicly accessible collection of facial expressions called FER2013 can be utilized for emotion recognition tasks. A total of 35,887 photos with a resolution of $48 \times 48$ pixels are therein the dataset. It is frequently used to train and test face expression recognition algorithms. It was developed by the Google Research team in 2013. A training set of 28,709 photos, a public test set of 3,589 photos, and a private test set of 3,589 photos make up the dataset. Seven facial expressions—anger, surprise, fear, sorrow, pleasure, disgust, and neutral—have been given to each photograph in the collection. The performance of FER2013, a well-liked benchmark dataset for facial expression recognition, is frequently discussed in academic articles and contests.

TABLE I: Training-Test-Validation Split in the dataset.

| **Overall Split in the dataset** | | |
|---|---|---|
| ***Training Set*** | ***Validation Set*** | ***Test Set*** |
| 28709 images | 3589 images | 3589 images |

### B. Experimental Setup

A laptop or a desktop computer with a camera and an internet connection are examples of IOT-enabled systems that could be used in this research. The suggested system is put into practise, along with model training, on a Google Cloud Nvidia Tesla K80 GPU (Colab Research)- an iPython notebook or Jupyter Notebook in a collaborative format. The implementation involves multiple libraries such as Dlib, a modern C++ toolkit; Theano; TensorFlow, an open-source software library for high-performance numerical computation, etc. In Google Colab, in the computer system, we capture the image of the person using the system's webcam. First, face landmarks are recognised. We use the webcam to capture an appearance, which we then instantly input into the system in real colour. On the output screen is shown the anticipated stress result.

### C. Performance Metrices

*1) Accuracy:* The number of accurate predictions to all the predictions made by a model on a given dataset is typically used to calculate accuracy. Accuracy is a popular fundamental evaluation metric defined in Equation (1). Accuracy is a commonly used evaluation metric in deep learning. It refers to the proportion of correctly classified instances from a dataset's total cases. In other words, accuracy assesses how effectively a model can anticipate each instance's label.

$$Accuracy = \frac{Correctly\ classified\ instances}{Total\ of\ instances} \tag{1}$$

For example, if a model correctly classifies 90 out of 100 instances, the accuracy can be calculated as accuracy = 90/100 = 0.9 or 90%. This means that the model has an accuracy of 90%, indicating that it can correctly predict the label of 90% of the instances in the dataset.

*2) Loss:* The loss metric is a measure of how well the model is performing on the training data. It determines the discrepancy between a specific training example's anticipated output and actual output. It is defined in Equation (2). It gauges how successfully the model can replicate the training set of data. A deep learning model's training objective is to reduce the loss function's value, which calls for the predicted output to be as close as feasible to the actual output. In most cases, the loss metric is a mathematical function that takes as inputs the projected output and the actual output and produces a single value that sums up the difference between both. Deep learning's most used loss metrics include mean squared error (MSE), mean absolute error (MAE), cross-entropy loss, and binary cross-entropy loss.

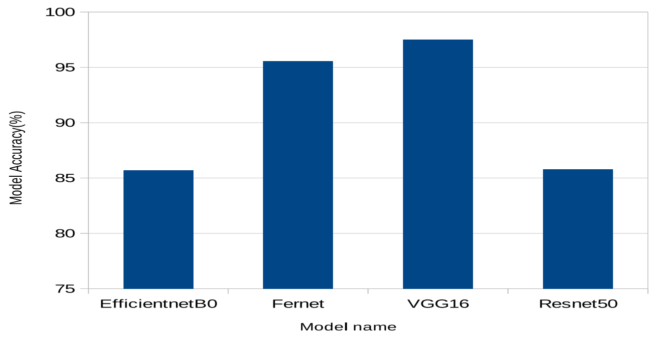
$$Loss = Predicted\ output - Actual\ Output \tag{2}$$

However, accuracy is not necessarily the appropriate criterion for assessing a deep learning model. The dataset may occasionally need to be more balanced, meaning each class has disproportionately varied occurrences. Under such circumstances, a model that forecasts the majority class for each instance could accomplish high accuracy but may be more helpful in practice. Therefore other evaluation metrics, such as precision, recall, and F1 score, may also be used to evaluate the performance of deep learning models, depending on the specific problem and dataset.

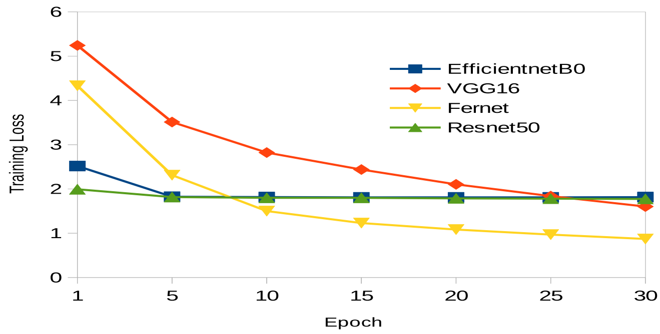
*3) Precision:* Precision is another performance metric that the suggested approach assesses. Precision is a performance statistic that counts the percentage of true positives (positive cases that were accurately anticipated) among all positive instances. It is defined in Equation (3). It reveals the proportion of positive incidents that occur when they are projected to be False positives (FP) are instances of negative data that were mistakenly projected as positive. In contrast, True Positives (TP) are cases of positive data that are accurately anticipated. Precision is a relevant statistic when the cost of a false positive prediction is substantial.

$$Precision = \frac{True\ positives}{True\ positives + False\ positives} \tag{3}$$

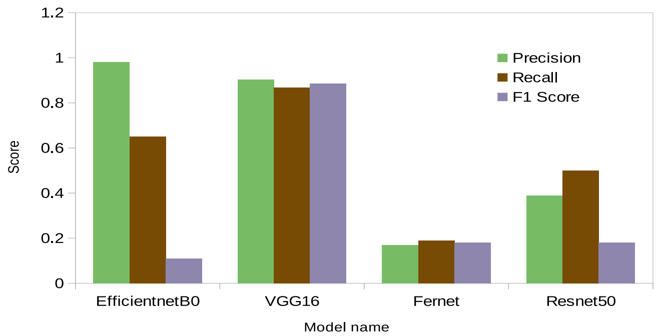
$$Recall = \frac{True\ positives}{True\ positives + False\ negatives} \tag{4}$$




(a) Accuracy




(b) Training Loss




(c) Precision, recall and F1 score

Fig. 5: Performance behaviour of the pre-trained Models

*4) Recall:* Recall is another performance indicator that quantifies the percentage of true positives (positive examples that were accurately predicted) across all positive instances. It reveals how many genuine positive examples the model adequately recognized. It is defined in Equation (4). False negatives (FN) are the number of positively predicted cases that occurred. When the cost of a false negative prediction is substantial, recall is an effective metric.

$$F1Score = 2.\frac{Precision.Recall}{Precision + Recall} \tag{5}$$

*5) F1 Score:* Another performance indicator, the F1-score, combines recall and precision into a single number. The comparison to evaluating accuracy or recall offers a more thorough assessment of a model's performance. An increase in the F1 score from 0 to 1 indicates improved performance;

TABLE II: Comparision analysis on models

| S.no | Author name | Approach | Accuracy(%) | Improvement value(%) |
|---|---|---|---|---|
| 1 | Ayten *et al.* [14] | KNN | 95.8 | 1.77 |
| 2 | Priyadarsini *et al.* [18] | FTT | 90 | 8.33 |
| 3 | Bikramjit et al. [17] | CNN Alexnet | 93.4 | 4.38 |
| 4 | Amogh *et al.* [24] | Viola-Jones algorithm | 79 | 22.78 |
| 5 | Eren *et al.* [23] | ANN | 96.26 | 1.28 |
| 6 | Samarasekara *et al.* [15] | CNN | 80 | 21.87 |
| 7 | **Our Approach** | **VGG16** | **97.5** | — |

further, the metric balances the trade-off between precision and recall or false positives and negatives. The metric is defined in Equation (5).

### D. Result Analysis

We evaluate our proposed stress detection method of four deep learning models, namely Efficientnetb0, Fernet, VGG16, and Resnet50. These models' analysis performance is based on accuracy and other relevant metrics mentioned above. The four pre-trained deep learning models undergo training and testing. They are fine-tuned to obtain accurate results. The training process utilized 80% of the available data. It is observed that the models produced promising results after 20 epochs of training. The models are then tested on the remaining 20% of the data left. The performance behaviour of these models is seen in Figure 5. As seen in Figure 5a, VGG16 model achieved the highest accuracy of 97.5% and EfficientnetB0 lowest 85.71 %. Figure 5b shows the training loss behaviour. The training loss ranges from 5.5 to 0.8 after 30 epochs, with the Fernet model achieving the lowest training loss of 0.4061 and EfficientnetB0 having the highest at 1.8114. These results demonstrate the effectiveness of the transfer learning approach and the potential of the pre-trained deep learning models used in the approach for accurate stress detection.

Figure 5c shows Precision, Recall, and F1-score values. EfficientnetB0 achieved the highest precision of 0.98, while Fernet achieved the lowest precision of 0.17. Regarding recall, VGG16 earned the highest recall of 0.8673, while Fernet got the most inadequate recall of 0.19. One can see that VGG16 achieves the highest F1 score of 0.8852, and Fernet offers the lowest F1 score of 0.18. Additionally, we evaluate our metrics with a confusion matrix. The matrix is used to calculate accuracy, precision, recall, and F1 score, which provide different insights into the performance of the classification model.

Performance in evaluation in two phases. The first phase is accomplished without normalization, and the next stage is complete after normalization. Figure 6 shows the confusion matrix without normalization for the model VGG16 for which we achieve the highest accuracy, and Figure 7 shows the confusion matrix after normalization for the model VGG16.

### E. Comparision Analysis

Table II presents a comparative analysis of different approaches/models for the stress detection task. The table compares the proposed approach with six prior strategies based on the accuracy metric. Our method can detect stress up to 22% more accurately than the selected previous approaches.

```
[[153   9 131 247 168 149 101]
 [ 23   1  10  22  20  19  16]
 [149  13 132 246 187 176 121]
 [231  30 233 409 360 332 179]
 [183  13 128 304 250 198 157]
 [174  18 169 282 222 222 160]
 [121  12  95 242 138 139  84]]
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Fig. 6: Confusion matrix of VGG16 without normalization

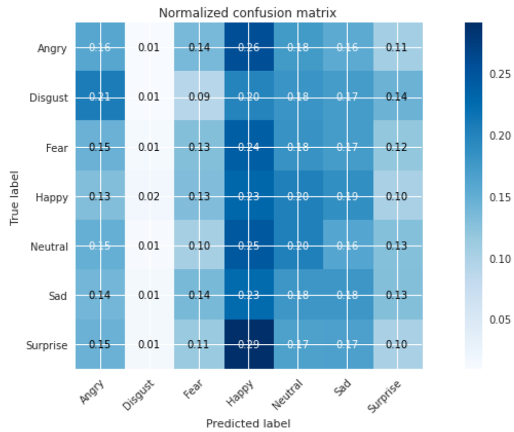


Fig. 7: Confusion matrix of VGG16 after normalization

It shows the stress detection method described in this paper outperforms many approaches presented in the literature. The results of the experiments have thus shown to be highly promising.

## V. Conclusion

This paper has suggested a novel method for detecting human stress using deep learning models based on image datasets of different emotional states. The proposed mechanism has employed four standard CNN models. Overall, the proposed approach has represented an exciting development in stress detection. Self-reports from the dataset's subjects gathered via several structured questionnaires can be used in future research. Also, new datasets can be introduced by combining the modalities—facial cues, logging data, audio/video recordings, etc.—that have been used in previous studies independently. Due to its near-complete inclusion of the elements required to induce stress in humans, a dataset of this kind can be used to identify stress more accurately.

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