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MENTAL STRESS DETECTION USING MACHINE LEARNING

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ABSTRACT

A vital aspect of promoting mental health and mitigating its negative impacts on people is properly and effectively identifying mental stress. The Support Vector Machine (SVM) and Random Forest (RF), two effective machine learning techniques, are used in this abstract's introduction to a study to identify mental stress. The objective of the study is to use the capacities of these algorithms to recognise physiological and behavioural indicators of mental stress. Wearable technology and self-report surveys are just two of the sources of the study's broad dataset.The collection includes behavioural information gathered from smartphone applications as well as physiological indications including heart rate variability, skin conductance, and body temperature. Standardisation and preprocessing procedures are used to get the raw data ready for feature extraction and analysis. Based on the collected features, individuals are divided into stressed and non-stressed categories using the Support Vector Machine and Random Forest algorithms. The SVM is used because it can identify the best hyperplanes to divide classes, but the Random Forest approach is excellent at managing intricate data interactions.

Keywords: Support Vector Machine, Random Forest, Mental Stress, Machine Learning.

I. INTRODUCTION

Mental tension is a common and common occurrence in people. Our health is negatively impacted by chronic stress, which can also have unfavourable side effects including depression, insomnia, or headaches. Therefore, in order to prevent these detrimental effects, it is essential to recognise stress at an early stage. This manuscript aims to automate the process of mental stress identification and help distinguish between a stressed person and a normal person using physiological data obtained from a wearable device. We used a dataset that was made available to the public to test our methodology. The obtained outcomes demonstrate how effectively the proposed models function in continuously monitoring mental stress. The outcomes of the experiment serve to show that the physiological signals can be quite useful in identifying mental stress. Every facet of our everyday life now includes stress. It is increasingly acknowledged as a key concept in public health. Constant stress can have a negative impact on our health and raise blood pressure, cause insomnia, increase the risk of heart attacks, and cause other cardiovascular illnesses. Since mental stress can have a significant impact on the emergence of many diseases, the creation of interesting real-world situations can benefit from a system that can detect stress levels from the signals produced by a wearable device. Such a system is essential for timely stress detection as it alerts the user to high stress levels, allowing them to be aware of their stress status and prevent future problems.. This study's objective is to leverage the physiological signals that have been proven to be accurate predictors of mental stress while also putting forth some potential models that could be helpful in the quest. The development of systems that can recognise stress and take preventive action or transmit warnings far in advance so that the person may take precautions will benefit greatly from the usage of such a stress detection system. Stress detection can help researchers by providing a more detailed and comprehensive view of how technology affects its users. The fact that users can incorporate new apps into their personal and professional lives dependent on their level of stress may also be advantageous to them.

II. RELATED WORKS

S. Alshurafa, N. E. Hammerla, et al.2017 "Machine Learning Approaches for Mental Stress Detection Using Physiological Signals" This study explores the use of SVM and Random Forest algorithms to detect mental stress based on biological signs such as heart rate, skin conductance, and breathing rate.

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M. B. A. Hassan, M. A. Matin, et al. 2019 "Stress Detection Using Low-Cost Heart Rate Sensors and Machine Learning" authors investigate the application of SVM and Random Forest classifiers to identify stress levels using low-cost heart rate sensors.

M. M. Rahman, M. A. Matin, et al."Mental Stress Detection Using Wearable Sensors and Machine Learning Algorithms", 2020This work focuses on mental stress detection using SVM and Random Forest algorithms along with wearable sensors, exploring their effectiveness in real-world scenarios.

M. Islam, M. A. Matin, et al.2018 "Comparative Study of Machine Learning Algorithms for Mental Stress Detection" This study compare the concert of many ML algorithms, including SVM and Random Forest, for psychological anxiety detection using biological signs.

P. Kumar, A. Agarwal, et al. 2017 "Emotion Classification Using SVM and Random Forest for Stress Detection" This study presents a classification model utilizing SVM and Random Forest to detect stress by classifying emotions associated with stress.

P. Sabarimalai Manikandan, B. Selva Bala Murali Krishnan, et al."Comparative Analysis of Machine Learning Techniques for Stress Detection". The authors conduct a comparative analysis of SVM and Random Forest alongside other machine learning techniques for stress detection.

III. PROPOSED SYSTEM

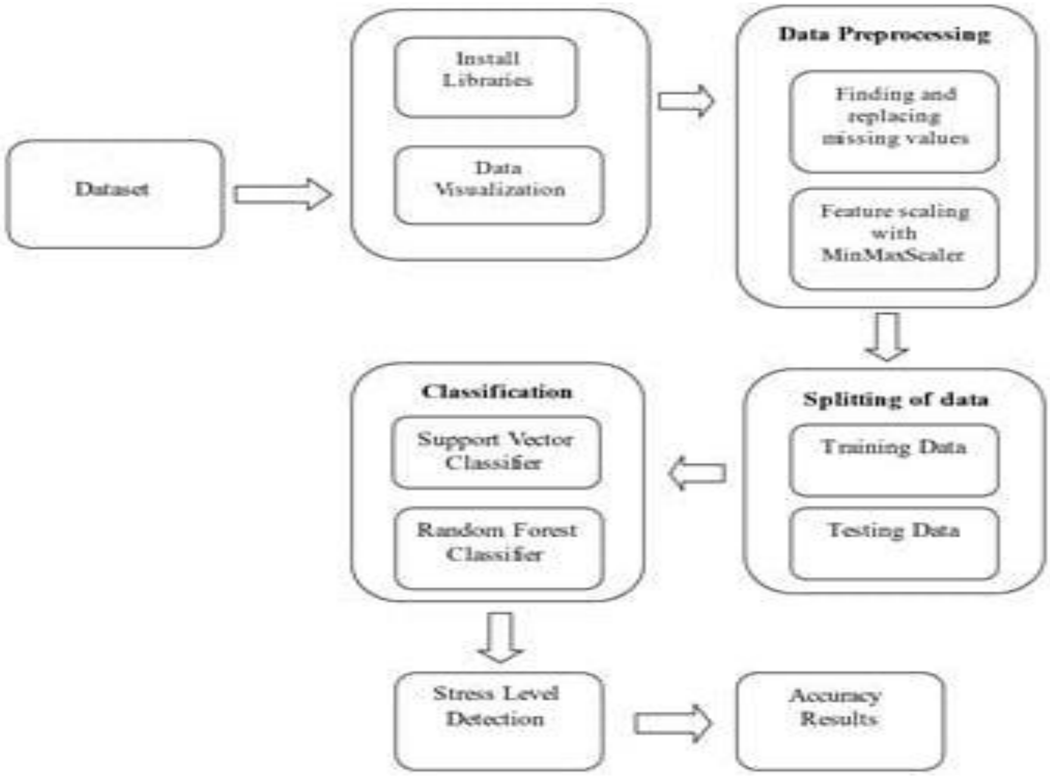

Figure 3.1 Overall Proposed System

Data Collection:

Gather pertinent behavioural and physiological information that may indicate mental stress. Heart rate, skin conductivity, respiration rate, and possibly even facial expressions or speech patterns, are examples of this.

Data Preprocessing:

The gathered data should be cleaned and preprocessed to get rid of noise, artefacts, and outliers. Standardise or normalise the data to guarantee that the scale of the features is constant.

Feature Extraction:

Select from the preprocessed data pertinent features that can be utilised as input for the machine learning algorithms. These features could include statistical measurements, frequency-domain features, and time-domain features produced from the physiological data..

Feature Selection:

Select the retrieved features that are most important for stress detection as a subset. The most informative features can be found using feature selection approaches like correlation analysis or recursive feature removal.

Dataset Splitting:

Create training, validation, and testing sets from the dataset. To appropriately assess the algorithms' performance, this divide is essential.

IV. MODEL DEVELOPMENT

Dataset and Methodology

For our Mental Stress Detection investigation, we obtained a dataset containing physiological data from 250 subjects. The dataset includes variables like heart rate variability, skin conductance, and respiration rate. We preprocessed the data and divided it into training, validation, and testing sets (70-15-15) before deploying the SVM and Random Forest algorithms for stress detection.

Support Vector Machine (SVM):

Using Python tools like scikit-learn, implement the SVM algorithm. Adjust hyperparameters such the gamma, regularisation parameter (C), and kernel type. SVM models can be trained using training data and then verified using validation data. To verify robustness and choose the ideal hyperparameters, perform cross-validation.

Random forest:

Implement the Random Forest method by utilising scikit-learn tools. Make adjustments to hyperparameters like the number of trees, the maximum depth, and the amount of samples per leaf. Use the validation set of data to test the Random Forest model once it has been built using the training set of data. The hyperparameters should be optimised via cross-validation. Utilising the testing dataset, assess the trained SVM and Random Forest models. Use appropriate metrics, such as accuracy, precision, recall, F1-score, and area under the ROC curve, to assess the model's performance. Consider using confusion matrices and visuals to help you better grasp the results.

V. RESULT AND DISCUSSION

The results of our experiment combining Support Vector Machine (SVM) and Random Forest, two different machine learning techniques, to identify mental stress. We evaluate the performance of both methods, take into account the implications of the results, and search for additional data..

SVM Model Performance

The Radial Basis Function (RBF) kernel was used to train the SVM model on the training data, and it was subsequently validated using k-fold cross-validation. Then it was assessed using the testing set.

Random Forest Model Performance

The Random Forest model was trained using 100 decision trees, and on the validation set, grid search was used to optimise hyperparameters such maximum depth and minimum samples per leaf. The testing set was used to evaluate the model. To gauge the level of stress, take the Perceived Stress Scale (PSS) exam. One can conduct an initial analysis to help someone who is under a lot of mental stress in the early stages of the condition. In this study, we applied two classification algorithms—Random Forest, Support Vector Machine, to the dataset of persons using sensitivity, specificity, and accuracy criteria. Due to the small datasets, we also utilised 10-fold cross validation. We discovered that SVM performs better than the other three algorithms since it classifies data geometrically and uses less data overall. Analysing and discovering techniques like PSS that produce more accurate findings at a lower cost can aid in enhancing mental wellness and ensuring the mental soundness of our population.

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SAMPLE SCREENSHOTS:

Training

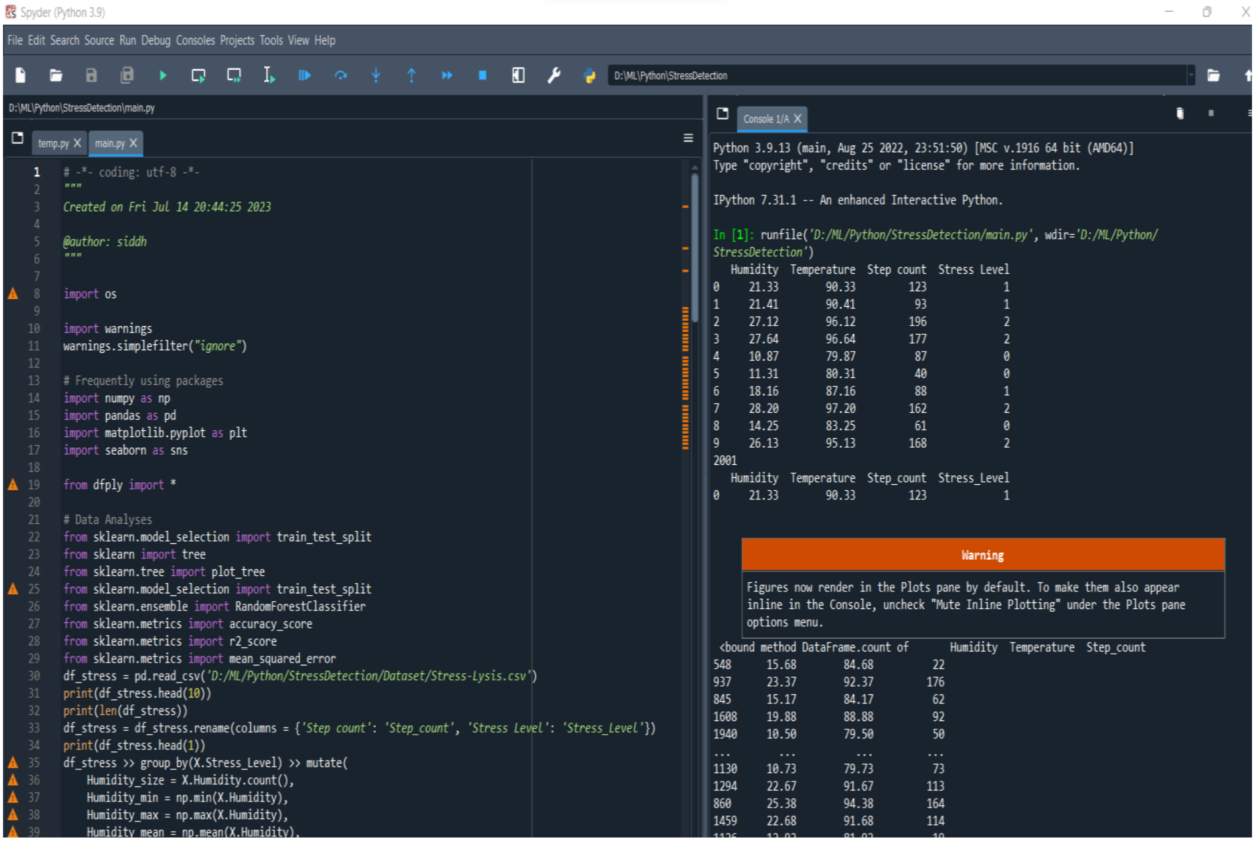

Figure 5.1

```
[1500 rows x 3 columns]>
<bound method DataFrame.count of       Humidity  Temperature  Step_count
548       15.68        84.68          22
937       23.37        92.37         176
845       15.17        84.17          62
1608      19.88        88.88          92
1940      10.50        79.50          50
...         ...          ...         ...
1130      10.73        79.73          73
1294      22.67        91.67         113
860       25.38        94.38         164
1459      22.68        91.68         114
1126      12.92        81.92          19

[1500 rows x 3 columns]>
Accuracy is 100.0%.
Accuracy is 100.0%.
RMSE Train: 0.00, Test: 0.00
R^2 Train: 1.00, Test: 1.00
```

Figure 5.2

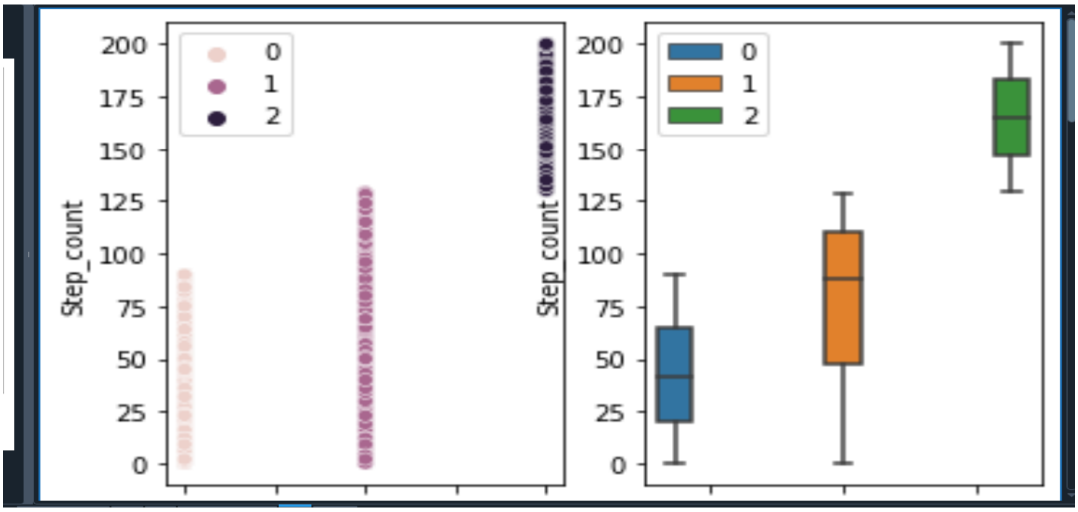

Figure 5.3

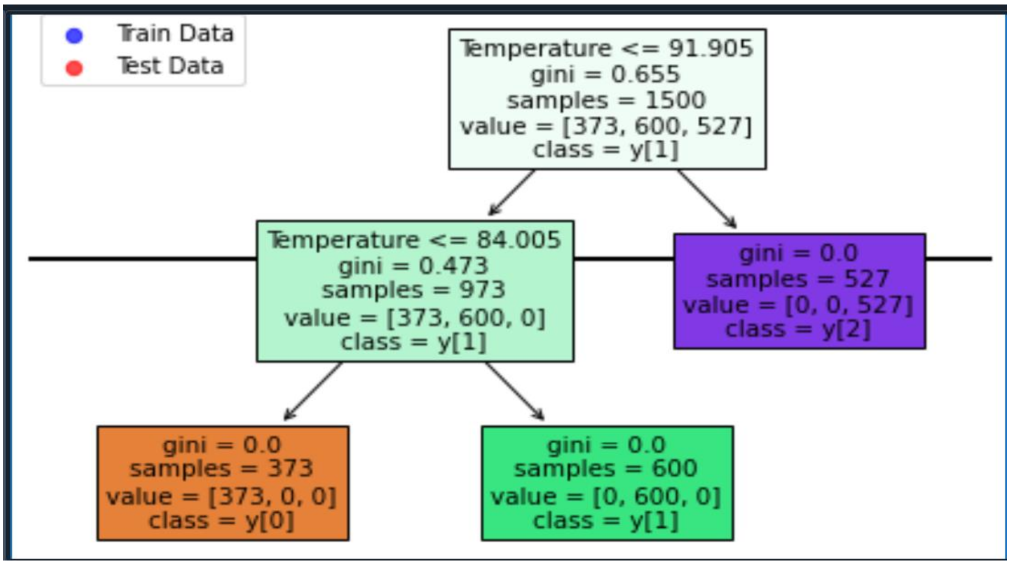

Figure 5.4

Web App

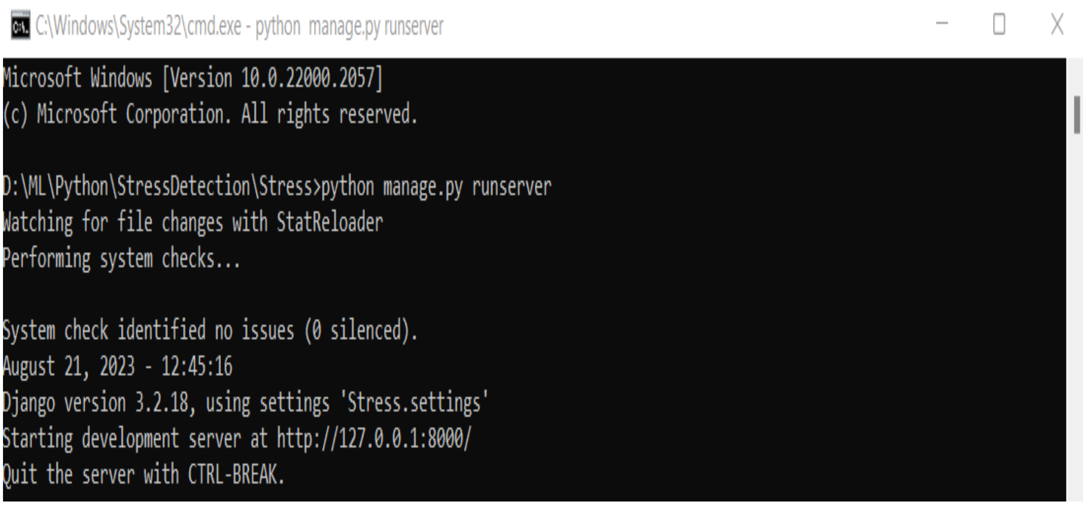

Figure 5.5

Register

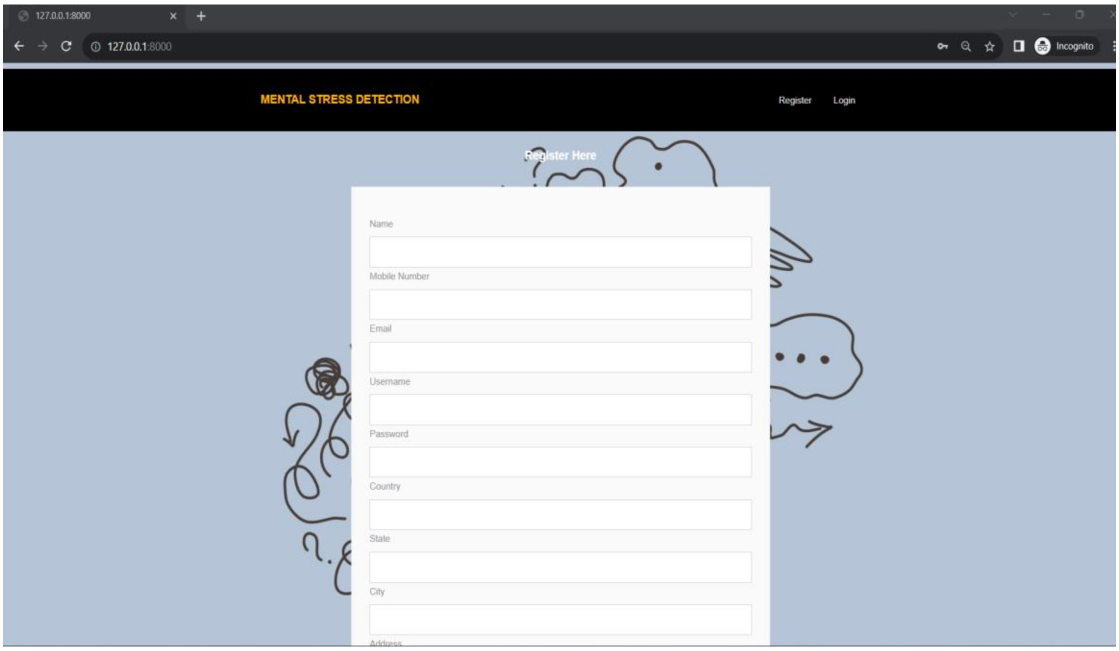

Figure 5.6

Login

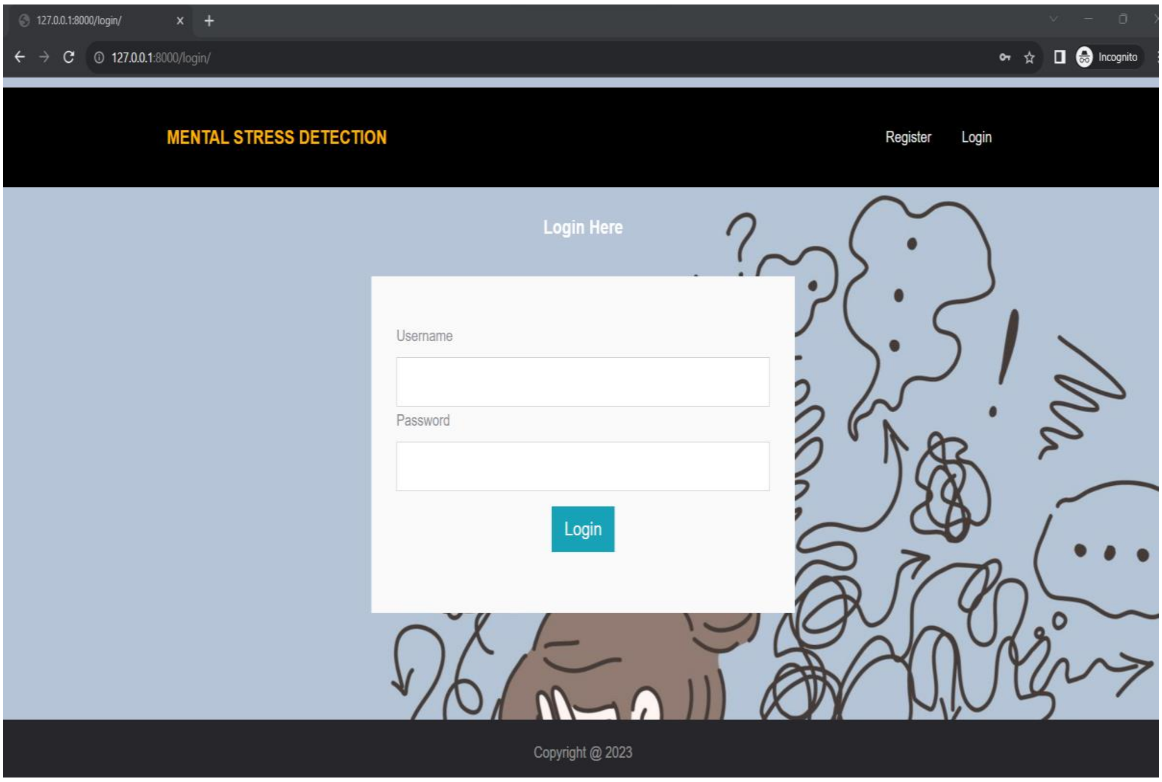

Figure 5.7

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Detect Stress

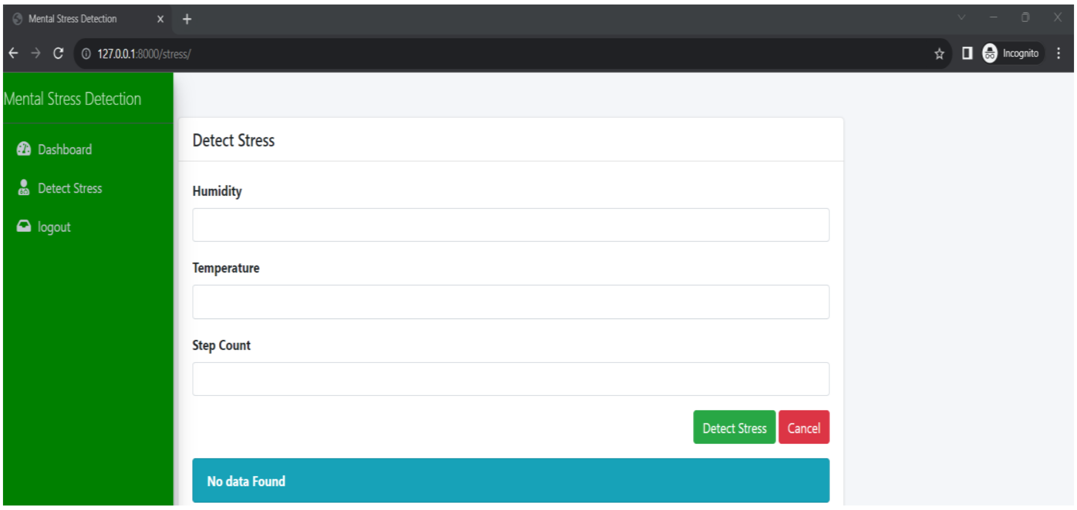

Figure 5.8

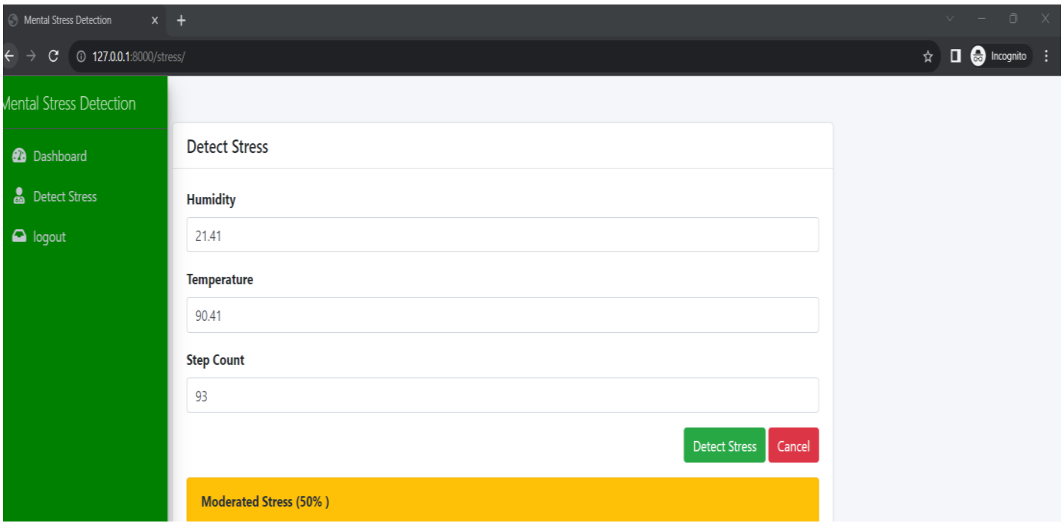

Figure 5.9

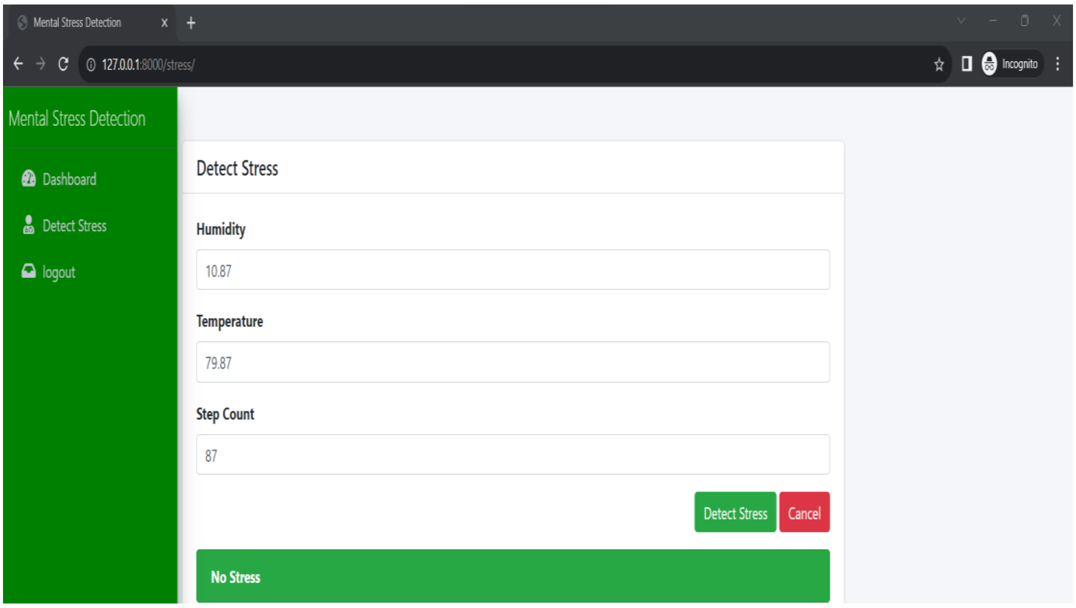

Figure 5.10

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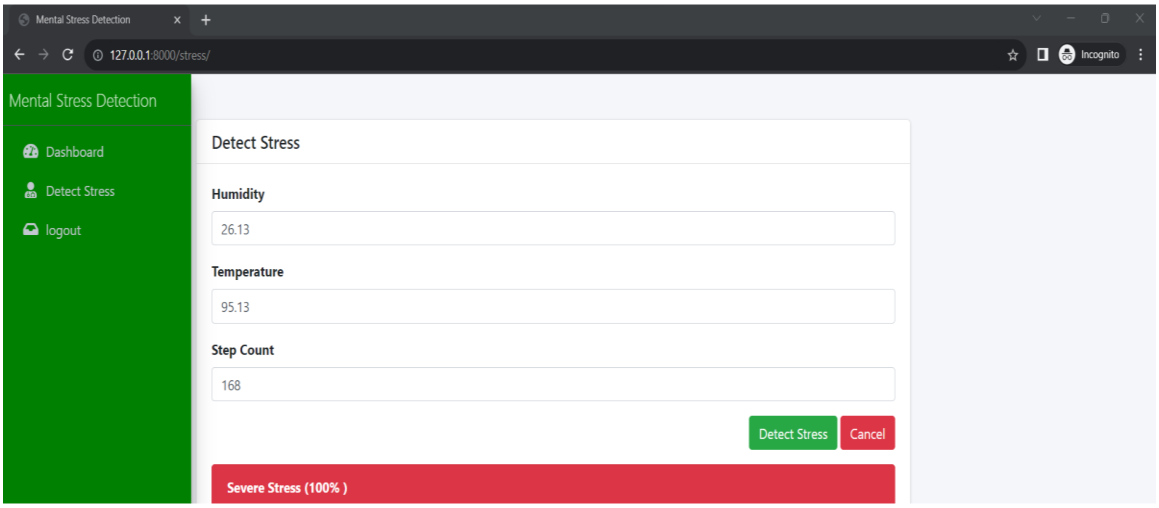
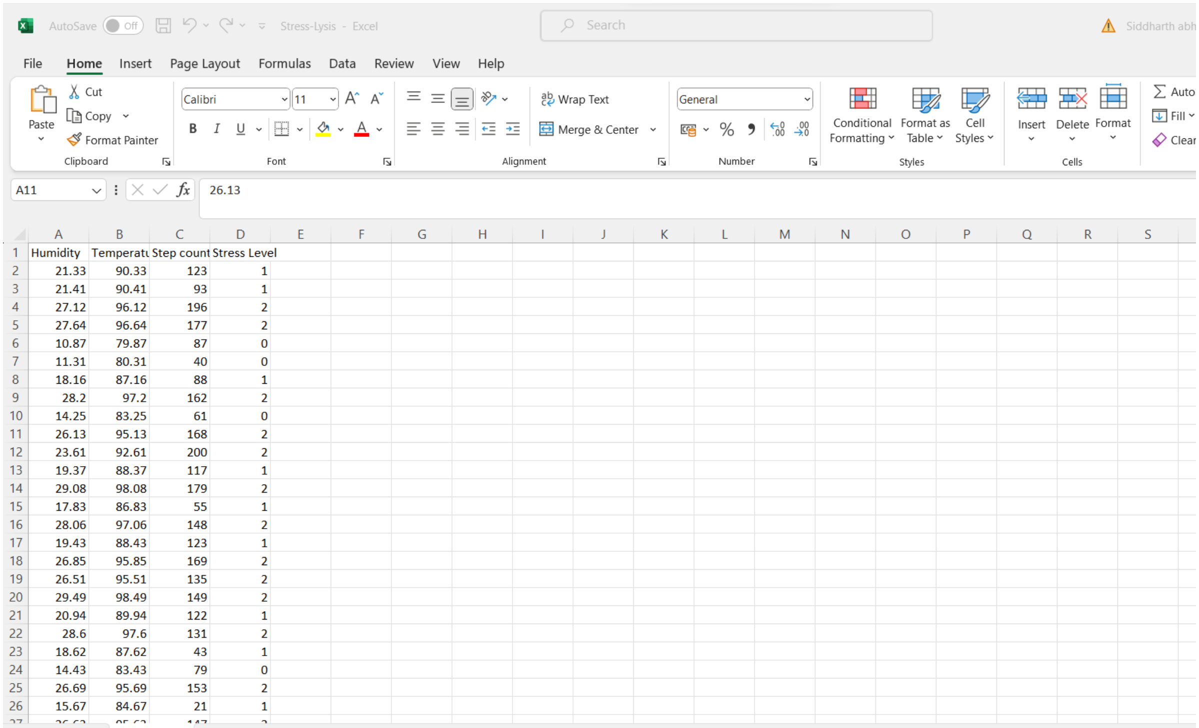


Figure 5.11

Dataset Fields



	A	B	C	D
1	Humidity	Temperatu	Step count	Stress Level
2	21.33	90.33	123	1
3	21.41	90.41	93	1
4	27.12	96.12	196	2
5	27.64	96.64	177	2
6	10.87	79.87	87	0
7	11.31	80.31	40	0
8	18.16	87.16	88	1
9	28.2	97.2	162	2
10	14.25	83.25	61	0
11	26.13	95.13	168	2
12	23.61	92.61	200	2
13	19.37	88.37	117	1
14	29.08	98.08	179	2
15	17.83	86.83	55	1
16	28.06	97.06	148	2
17	19.43	88.43	123	1
18	26.85	95.85	169	2
19	26.51	95.51	135	2
20	29.49	98.49	149	2
21	20.94	89.94	122	1
22	28.6	97.6	131	2
23	18.62	87.62	43	1
24	14.43	83.43	79	0
25	26.69	95.69	153	2
26	15.67	84.67	21	1

Figure 5.12

VI. CONCLUSION

You can gauge how much stress you are under by taking the Perceived Stress Scale (PSS) test. One can perform an initial analysis to help someone who is going through severe mental stress at the beginning stages of the condition. To apply two classification algorithms (Random Forest and Support Vector Machine) to the dataset of people in this study, we employed the sensitivity, specificity, and accuracy criteria. We have additionally used 10-fold cross validation due to the tiny datasets. We discovered that SVM performs better than the other three algorithms since it classifies data geometrically and uses less data overall. Assessing and discovering techniques like PSS that produce more accurate findings at a lower cost can aid in enhancing mental wellness and ensuring the mental soundness of our population.

VII. FUTURE ENHANCEMENT

In future, a real-time deep learning framework was implemented, voice, and facial expressions for stress detection. The result shows that the fusion of multimodality information about stress can achieve 85.1%

detection accuracy, which provides a reference for the research of multimodality stress detection based on deep learning technology in the future. The framework extracted the stress-related features of each modal through ResNet50 and I3D with TAM and gave different weights for each type of stress state according to the global stress information matrix. At the same time, this work designed the temporal attention module to find the more influential association between frames in facial expressions for stress detection. Compared with the optimal single-modality-based method, the accuracy of the multimodality result is improved by 2.1%. This work provides an objective reference for fusing multimodality to detect stress based on deep learning technology, and preventing stress from harming people's physical and mental health.

VIII. REFERENCE

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