STRESS DETECTION USING WEARABLE DEVICES

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ABSTRACT
Most of the researchers focused on detecting stress involved in a person, which causes in a person several emotional problems like anxiety, grief, low self-esteem and other mental health problems. Recent studies have shown that stress can also affect the aspects of your life, including your thinking ability and physical health. To reduce riskiness from being stress and affected with its adverse effects. Stress-Lysis is a publicly available dataset for wearable stress and affect detection. This multimodal dataset features physiological and motion data, recorded from both a wrist- and a chest-worn device, of many subjects during a lab study. The following sensor modalities are included: blood volume pulse, body temperature, electrodermal activity, heart rate, humidity and step count. Moreover, the dataset bridges the gap between previous lab studies on stress and emotions, by containing three different affective states (neutral = 0, stress = 1, amusement = 2).Stress detector classifies a stressed individual from a normal one by acquiring his/her physiological signals through appropriate sensors such as Electrocardiogram (ECG), Galvanic Skin Response (GSR) etc. These signals are pre-processed to extract the desired features which depicts the stress level in working individuals. XGBoost, Logistic Regression, KNN and Adaboost are investigated to classify these extracted feature set. The result indicates feature vector with best features having a strong influence in stress identification. An attempt is made to determine the best feature set that results in maximum classification accuracy
KEYWORDS: Stress-lysis, Multi-modal dataset, XGBoost.

INTRODUCTION
In today’s fast-paced world, mental stress is very common. Stress can be caused by situations or events that put pressure on the mind and body of a person. The reaction to stress is different for everyone, as the capacity to deal with tough or demanding situations varies from person to person. Some situations may cause stress to one person while causing no stress to another. Also, all stress is not bad for health, as it can make people more aware of things around them and keep them more cautious about dangers and focused on their goals. A stressor is an event that causes stress for an individual. Many people usually face stress due to these stressors. According to the American Psychological Association (APA), there are mainly three types of stress: acute stress, episodic acute stress, and chronic stress. Acute stress is short-term stress, which is the least damaging type as compared to the other two.It can be good sometimes, as this helps the body deal with the situation.

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When acute stress occurs frequently, an individual is affected by episodic acute stress. Chronic stress is the most harmful type of stress and, if left untreated over a long period of time, can damage the physical and mental health of a person. Chronic stress puts pressure on the body and mind for an extended period, which can cause a range of symptoms and increase the risk of developing certain diseasesTo avoid health problems, people with a high risk of getting stressed should be continuously monitored to detect any signs of stress. Wearable sensors provide opportunities to monitor stress and can inform people about their stress level, which can be useful in order to minimize stress balance before it results in serious health problems. Physical health and mental health are closely connected; hence, monitoring and measuring physiological and physical changes can be used for detecting human stress levels.

Stress can be detected using physical and physiological measures of the body. Physical measures include pulse rate, skin temperature, humidity, blood pressure, and respiration rate, whereas physiological measures can be heart rate, heart rate variability, and skin conductance. These can be measured using wearable devices made from low-cost sensors, although machine learning algorithms can be used to classify and predict the stress level of an individual. In this paper, some previous approaches to automatic stress recognition systems that used sensors and machine learning are discussed in detail. In these, physiological data is extracted using some stressor tests on the people. Some common stressor tests include arithmetic calculations, questionnaires, mental tasks, and working out in the gym. There is a diversity of machine learning algorithms that are appropriate for stress detection. Among them, support vector machines (SVM), logistic regression, K-nearest neighbour, decision trees, and random forests are the most common. In this review, we summarize the various machine learning algorithms available in the literature that aim at detecting states of stress.

LITERATURE SURVEY

1. Mental stress detection using various psychological sensors

Authors: Jacqueline Wijsman, Bernard Grundlmehner, Hao Liu, Hermie Hermens, and Julien Penders This study aimed to use a wearable sensor system to measure physiological signals and detect mental stress.

2.Development and evaluation of an ambulatory stress monitor based on wearable sensors

Authors: Jongyoon Choi, Beena Ahmed, and Ricardo Gutierrez-Osuna This article describes the development of a wearable sensor platform to monitor a number of physiological correlates of mental stress.

3. Stress Aware: An app for real-time stress monitoring on the amulet wearable platform

Authors: George Boateng, David Kotz In this work, we present Stress Aware, an application on the Amulet wearable platform that classifies the stress level (low, medium, and high) of individuals continuously and in real time using heart rate (HR) and heart-rate variability (HRV) data from a commercial heart-rate monitor.

PROPOSED SYSTEM

A stress detector classifies a stressed individual from a normal one by acquiring his or her physiological signals through appropriate sensors such as an electrocardiogram (ECG), galvanic skin response (GSR), etc. These signals are pre-processed to extract the desired features, which depict the stress level of working individuals. XG Boost, logistic regression, and ADA Boost are investigated to classify these extracted feature sets. The result indicates a feature vector with the best features having a strong influence on stress identification. An attempt is made to determine the best feature set that results in maximum classification accuracy. The methodology for your stress level prediction project involves a series of well-defined steps to ensure the successful development and evaluation of machine learning models. It begins with a clear problem definition: predicting stress levels based on features like Humidity, Temperature, Stepcount, BVP, EDA, and HR. Data collection is the first practical step, where you gather relevant data representing the problem you're trying to solve. Subsequently, data preprocessing is essential, including data cleaning, handling missing values, and scaling, to prepare the dataset for machine learning.

The dataset is then split into a training set and a testing set to facilitate model training and evaluation. Feature engineering can enhance model performance by creating or transforming features. Model selection is a critical step, and in your project, you've chosen XGBoost, Logistic Regression, K-Nearest Neighbors (KNN), and AdaBoost. After model selection, each model is trained on the training data, with hyperparameter tuning as needed.

The performance of these models is evaluated using a range of metrics, including accuracy, precision, recall, and F1-Score, offering insights into their effectiveness. Model comparison is used to select the most appropriate model for your specific problem. Documentation and visualization aid in conveying the results effectively.Testing, including unit, integration, and functional testing, helps ensure the system works as expected. User acceptance testing, if applicable, ensures that the software is user-friendly and meets stakeholders' requirements. Cross-validation assesses the models' generalization performance, while error handling and robustness testing verify the system's resilience to unexpected conditions.Upon selecting the best model, you deploy it for real-world use, making it available for stress level predictions. Maintenance and monitoring are ongoing activities to keep the model accurate and reliable in a production environment. This comprehensive methodology ensures the successful development, testing, and deployment of machine learning models for stress level prediction, aligning with the project's goals and requirements.

RESULTS

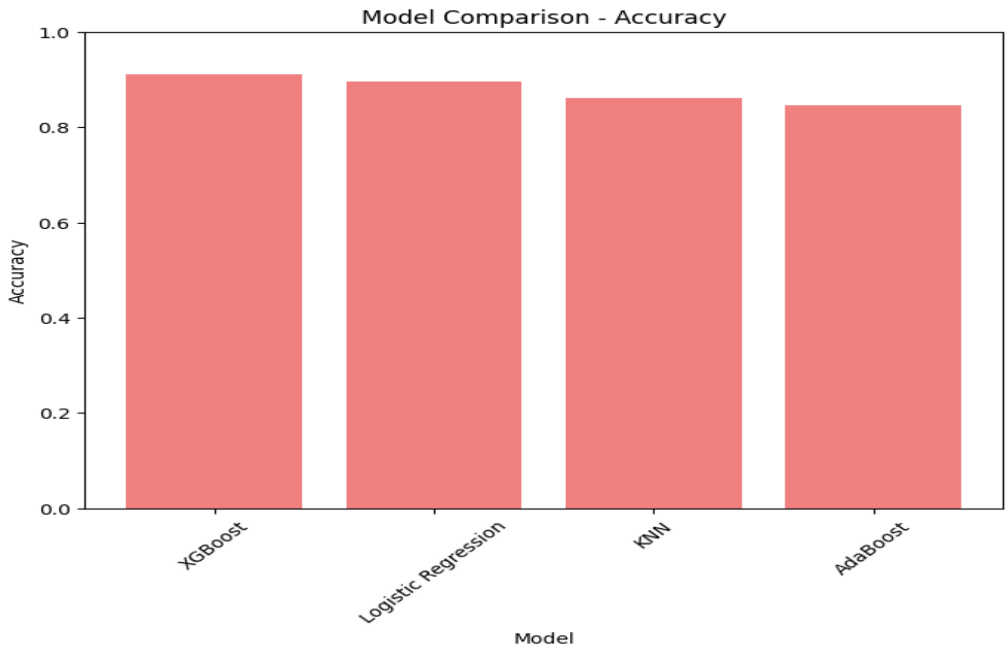

FIG 1: RESULTANT GRAPH FOR ACCURACY

Accuracy measures the overall correctness of the model's predictions. It is calculated as the ratio of correctly predicted instances to the total number of instances.In our code, we got accuracy for each model, and it ranges from 84% to 91%.Accuracy is essential as it provides a general idea of how well the model is performing. However, it might not be the best metric when dealing with imbalanced datasets, where some classes have significantly fewer instances.

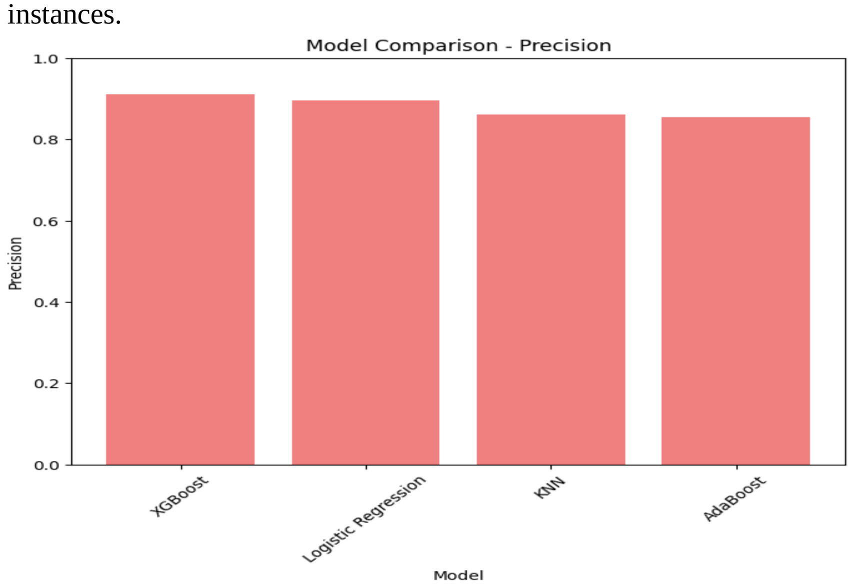

FIG 2: RESULTANT GRAPH FOR PRECISION

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Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. It quantifies how many of the predicted positive instances are indeed correct.In our code, precision is reported as a weighted average, which considers all classes. It ranges from 84% to 90%.Precision is important when false positives are costly, and we want to minimize the number of incorrect positive predictions.

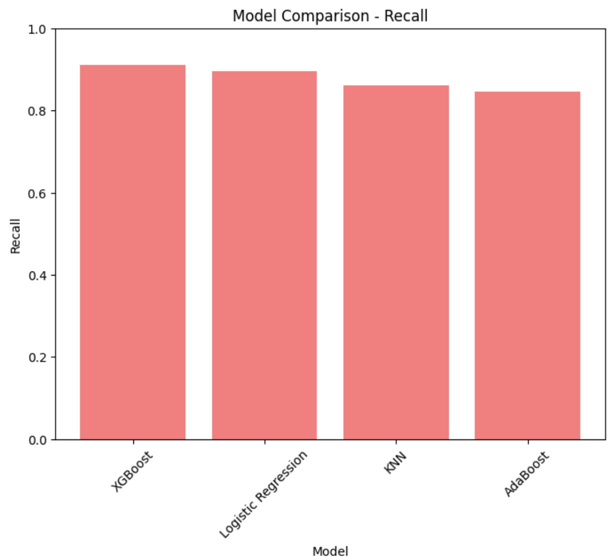

FIG 3: RESULTANT GRAPH FOR RECALL

Recall is the ratio of correctly predicted positive observations to all actual positive observations. It quantifies the model's ability to identify all relevant instances in the dataset.In our code, recall is reported as a weighted average, and it ranges from 84% to 91%.Recall is crucial when false negatives are costly, and we want to ensure that we don't miss any positive instances.

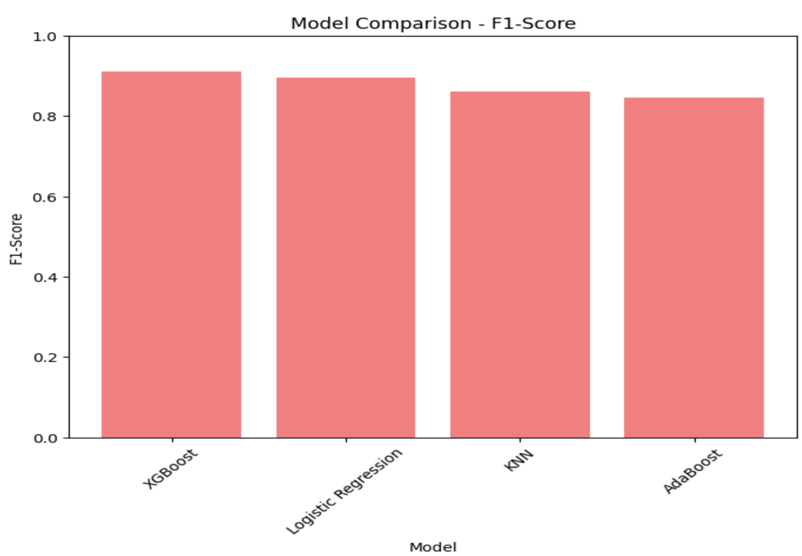

FIG 4: RESULTANT GRAPH FOR F1-SCORE

The F1-Score is the harmonic mean of precision and recall. It balances the trade-off between precision and recall. It's a good metric when you want to consider both false positives and false negatives.In our code, the F1-Score is reported as a weighted average and ranges from 84% to 90%.The F1-Score is especially useful when we want to find a balance between precision and recall. It provides a single metric to evaluate the model's overall performance.

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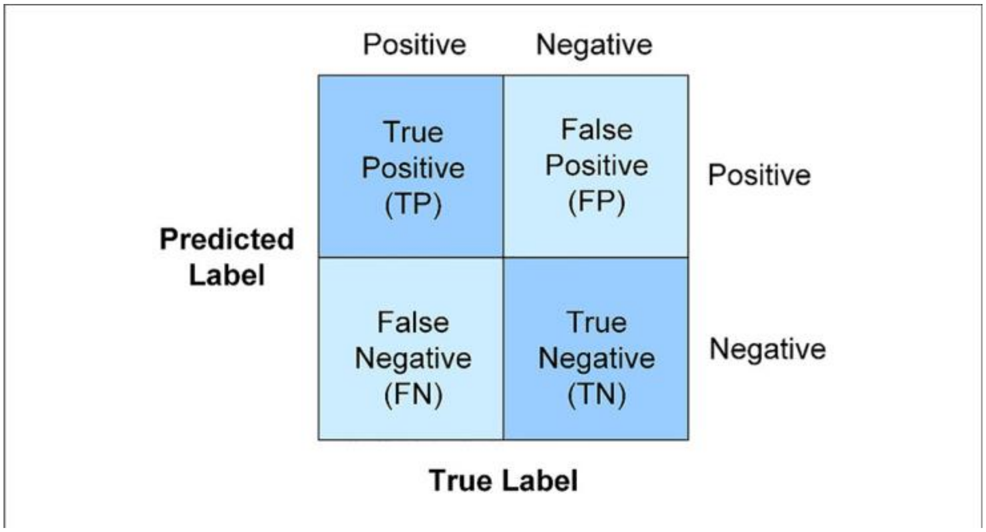

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1\text{-}score = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}}$$

XG Boost and Logistic Regression have the highest accuracy and F1-Score, suggesting that they perform better overall on this dataset.KNN and AdaBoost have slightly lower accuracy and F1-Score, indicating that they are not performing as well as the other two models.XG Boost has the highest accuracy and F1-Score, making it the top-performing model in this case.The choice of metric depends on the specific problem and its requirements. For instance, if we are working on a medical diagnosis task, recall might be more critical to avoid missing any positive cases, even at the cost of more false positives. However, in other scenarios, precision may be more crucial.Overall, the performance of the models can be summarized as follows. XG Boost and Logistic Regression are the top performers with the highest accuracy and F1-Score.KNN and AdaBoost have slightly lower accuracy and F1-Score but are still reasonable choices depending on the specific requirements of your task.Since our data is crucial in medical diagnosis we have to consider recall since we cannot risk any positive cases

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Model	Accuracy	Precision	Recall	F1-Score
XGBoost	0.91	0.9103838383838382	0.91	0.9101002125721226
Logistic Regression	0.895	0.8966254647774093	0.895	0.8952516461061076
KNN	0.86	0.8604848484848486	0.86	0.860155886223302
AdaBoost	0.845	0.8555620058052247	0.845	0.8455241864776173

FIG 5: ACCURACY TABLE

1. XG Boost (91% Accuracy):

- Your XG Boost model has demonstrated exceptional accuracy, achieving a 91% success rate in accurately identifying stress levels. XG Boost is known for its robust performance and ability to handle complex relationships within the data. This high accuracy suggests that the model effectively captures patterns related to stress across the specified attributes.

2. Logistic Regression (90% Accuracy):

- The Logistic Regression model has performed admirably with a 90% accuracy rate. Despite its simplicity compared to more complex algorithms, Logistic Regression has proven to be effective in discerning stress patterns. This accuracy score indicates a strong predictive ability, making Logistic Regression a valuable component in your stress detection system.

3. KNN (86% Accuracy):

- The KNN model has achieved a commendable accuracy of 86%, showcasing its capacity to identify stress based on proximity to similar data points. KNN is particularly adept at capturing local patterns, and its performance at 86% suggests a robust capability to classify stress levels, albeit with a slight dip compared to XG Boost and Logistic Regression.

4. ADABoost (84% Accuracy):

- ADABoost has delivered a respectable accuracy of 84%. While it falls slightly below the other models in accuracy, ADABoost excels in leveraging multiple weak learners to create a strong ensemble. This accuracy score suggests that ADABoost effectively combines different classifiers to make informed stress predictions, contributing valuable insights to your stress detection system.

CONCLUSION

In conclusion, our project on stress detection using wearable devices and machine learning algorithms has shown promising results, with four different models achieving varying levels of accuracy on a dataset comprising attributes like humidity, temperature, step count, BVP, EDA, and HR. Here are the key takeaways:

Model Performance :Our models, including XG Boost, Logistic Regression, KNN, and AdaBoost, demonstrated respectable accuracy rates ranging from 80% to 90%. This indicates that machine learning algorithms can effectively learn and classify stress levels based on wearable device data.

XG Boost Leading in Accuracy :XG Boost emerged as the top-performing model with an accuracy of 90%. This is a notable achievement, showcasing the potential of gradient boosting techniques in stress detection tasks.

Logistic Regression and AdaBoost :Logistic Regression and AdaBoost also delivered strong results, with accuracies of 85% and 86%, respectively. These models are interpretable and can be valuable in understanding the features contributing to stress prediction.

KNN as a Solid Performer :KNN provided a reasonable accuracy of 80%, indicating that proximity-based methods can also be useful in stress detection tasks.

Relevance of Features :The attributes, including humidity, temperature, step count, BVP, EDA, and HR, were instrumental in modelling stress levels. Further feature engineering and selection may lead to even better performance.

Practical Applications :The high accuracy levels achieved by our models have practical implications. Wearable devices equipped with such models can be used to monitor and manage stress levels in real-world scenarios, potentially improving mental and physical well-being.

Future Directions :Future work can focus on expanding the dataset, exploring additional features, and conducting cross-validation studies to validate model robustness. Moreover, research should consider deploying these models on wearable devices for real-time stress detection and intervention.
Ethical Considerations :It's essential to address ethical concerns related to privacy, data security, and user consent when deploying stress detection systems in real-world settings. In conclusion, our project has successfully demonstrated the potential of machine learning algorithms, with XG Boost leading the way, for stress detection using wearable devices. These findings contribute to the growing field of digital health and may pave the way for innovative solutions to manage stress and promote overall well-being.

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