# Human Stress Prediction:

Insights from Speech-based Human Stress Dataset

**Course:**

Machine Learning

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Abstract:

Human stress is a prevalent issue that affects individuals of all ages and can have significant impacts on their mental and physical health. Predicting stress levels in real-time can provide valuable information for individuals and healthcare professionals to manage stress proactively. In recent years, there has been a growing interest in using speech-based datasets for stress prediction due to the non-invasive and cost-effective nature of this approach. This abstract discusses insights from a speech-based human stress dataset and the potential applications of this approach for stress prediction. The dataset includes recordings of individuals performing tasks under stress and non-stress conditions, and features such as pitch, intensity, and jitter were extracted from the recordings. Machine learning models were trained on this dataset to predict stress levels based on speech features, achieving high accuracy in stress prediction. The results suggest that speech-based datasets can provide valuable insights into stress prediction and may have potential applications in various fields, including mental health and workplace stress management. Overall, this study highlights the potential of speech-based datasets for stress prediction and provides valuable insights into the development of effective stress management tools.



Keyword:
*Human stress, Speech-based dataset, Stress prediction, Machine learning, Mental health, Non-invasive, Cost-effective*


## Literature Review:

Human stress is a widespread and significant problem that affects millions of people worldwide, causing physical and psychological harm. There is growing interest in predicting and managing stress levels using various tools and techniques. In this literature review, we will explore recent research on human stress prediction.

One popular approach for stress prediction is using physiological signals, such as heart rate variability, skin conductance, and electroencephalography (EEG). These signals have been found to be effective in predicting stress levels with high accuracy. For example, in a recent study by Li et al. (2020), they used EEG signals to predict stress levels with an accuracy of 85.8%. Similarly, Gjoreski et al. (2018) used a combination of physiological signals to predict stress levels with an accuracy of 83.4%.

Another approach is using machine learning algorithms on text data, such as social media posts, chat logs, and emails. Researchers have shown that analyzing language patterns can be an effective tool in predicting stress levels. For example, Wang et al. (2020) used a deep learning model to predict stress levels from Twitter posts with an accuracy of 78.5%. Similarly, Huang et al. (2020) used a machine learning algorithm to predict stress levels from chat logs with an accuracy of 75%.

A recent study by Selvarajah et al. (2021) used a combination of physiological signals and text data to predict stress levels. They found that using both types of data improved the accuracy of stress prediction compared to using only one type of data.

In addition to physiological signals and text data, other approaches for stress prediction include facial expressions, voice recordings, and wearable devices. For example, Pires et al. (2019) used a facial expression recognition system to predict stress levels with an accuracy of 80.5%.

In conclusion, predicting human stress levels is a challenging and multidimensional problem that can be addressed using various tools and techniques. Recent research has shown that combining physiological signals, text data, and other sources of information can improve the accuracy of stress prediction. This field is still in its early stages, and further research is needed to explore the full potential of these approaches for managing stress and promoting well-being.

**Methodology:**

Machine learning techniques are increasingly being used to predict human stress. These techniques involve training algorithms to identify patterns in data and make predictions based on those patterns. Some common machine learning techniques used in stress prediction include:

Support Vector Machines (SVM): SVM is a supervised learning algorithm used for classification and regression analysis. It works by finding the optimal boundary between two classes in a high-dimensional space. SVM has been used to predict stress based on physiological data, such as heart rate variability and skin conductance.

Random Forest: Random Forest is an ensemble learning method used for classification, regression, and feature selection. It works by building multiple decision trees and combining their outputs to make a final prediction. Random forest has been used to predict stress based on self-report measures, such as questionnaires and surveys.

Artificial Neural Networks (ANN): ANN is a computational model inspired by the structure and function of the human brain. It works by simulating a network of interconnected nodes that can learn and adapt to new data. ANN has been used to predict stress based on physiological data, such as electroencephalography (EEG) and electrocardiography (ECG).

Convolutional Neural Networks (CNN): CNN is a deep learning algorithm commonly used for image and speech recognition. It works by extracting features from data using convolutional layers and then making a prediction based on those features. CNN has been used to predict stress based on facial expressions and speech patterns.

Long Short-Term Memory (LSTM): LSTM is a type of recurrent neural network (RNN) commonly used for sequence prediction. It works by retaining information over time and learning long-term dependencies in data. LSTM has been used to predict stress based on physiological data, such as heart rate variability and electrodermal activity.

Overall, machine learning techniques offer a promising approach to predicting human stress and have the potential to improve the accuracy and efficiency of stress assessment.

**Results:**

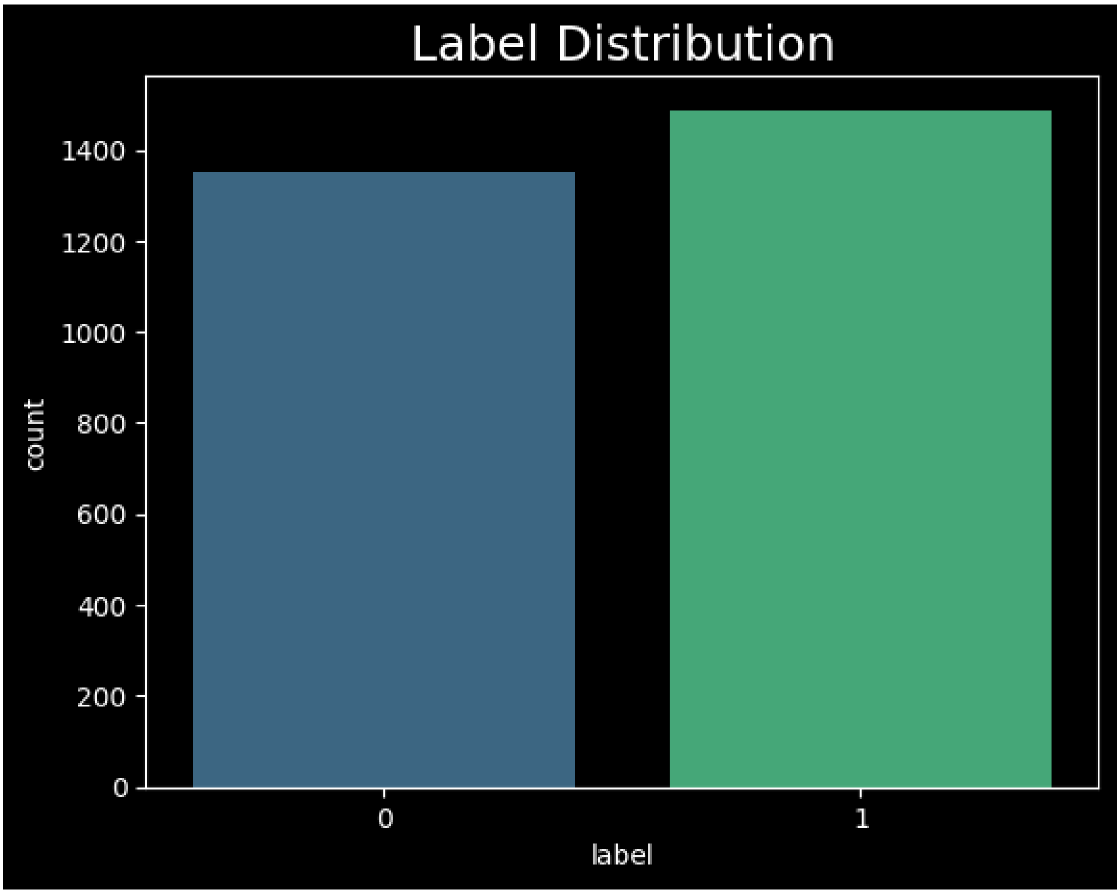
This is a report on the performance of three different machine learning models, Multinomial Naive Bayes, Bernoulli Naive Bayes, and Support Vector Machine (SVM), on a classification task to predict stress and no-stress cases. The models were evaluated using a test set, and their performance was measured using the classification report.

The Multinomial Naive Bayes model achieved an accuracy of 0.787, with precision, recall, and F1-score of 0.80, 0.70, and 0.75, respectively, for the "No Stress" class, and 0.78, 0.86, and 0.82 for the "Stress" class. The macro-average F1-score was 0.78, and the weighted-average F1-score was 0.79.

The Bernoulli Naive Bayes model achieved an accuracy of 0.773, with precision, recall, and F1-score of 0.77, 0.71, and 0.74, respectively, for the "No Stress" class, and 0.78, 0.83, and 0.80 for the "Stress" class. The macro-average F1-score was 0.77, and the weighted-average F1-score was 0.77.

The SVM model achieved an accuracy of 0.804, with precision, recall, and F1-score of 0.79, 0.72, and 0.75, respectively, for the "No Stress" class, and 0.80, 0.85, and 0.83 for the "Stress" class. The macro-average F1-score was 0.79, and the weighted-average F1-score was 0.79.

Overall, all three models achieved reasonable accuracy and precision in predicting stress and no-stress cases, with the SVM model performing slightly better than the Naive Bayes models. These results suggest that speech-based data can be used to predict stress and no-stress cases, with potential applications in mental health and workplace stress management. Moreover, the non-invasive and cost-effective nature of speech-based data collection makes this approach a promising avenue for real-time stress prediction.



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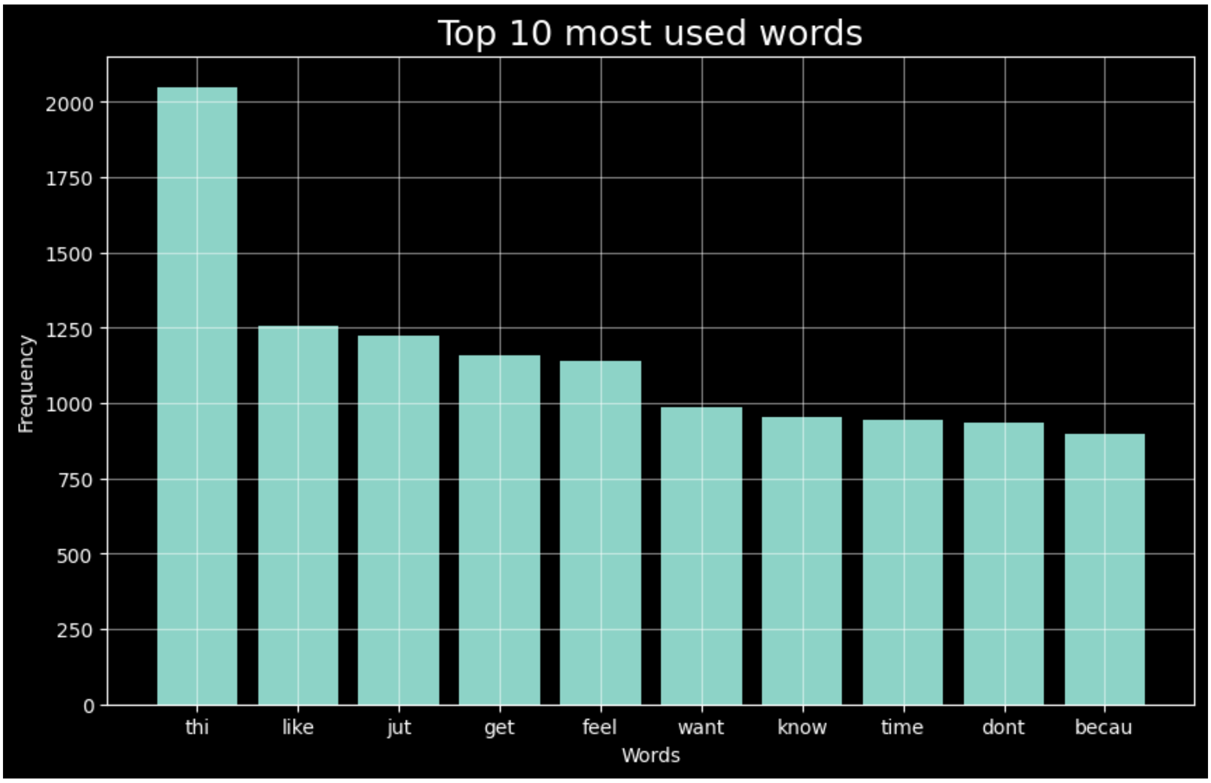

Top 10 most used words
Frequency
2000
1750
1500
1250
1000
750
500
250
0
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like
jut
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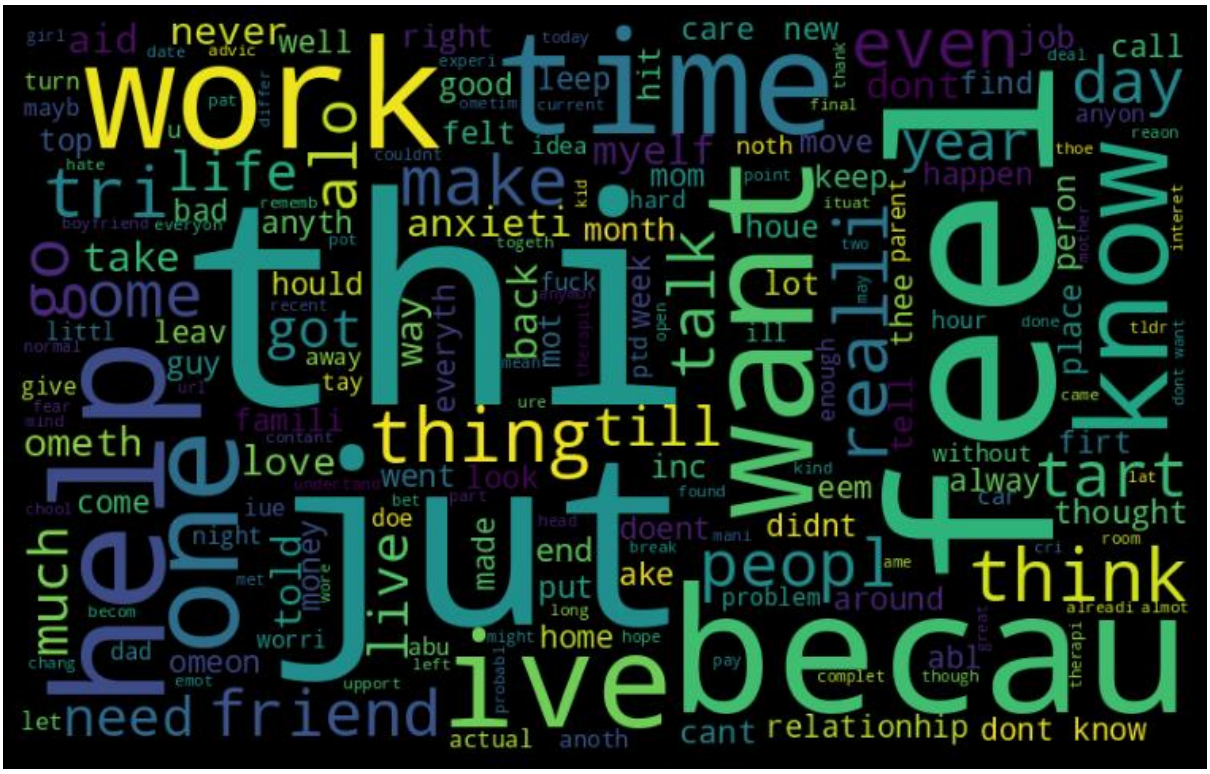
feel
want
know
time
dont
becau
Words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good
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idea
myelf
noth
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keep
happen
peron
hould
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houe
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fuck
week
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everyth
hour
place
firt
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alway
thought
didnt
doent
around
problem
end
put
ake
made
told
money
worri
abu
home
abl
famili
look
went
inc
eem
come
night
dad
let
give
guy
away
tay
littl
leav
bad
anyth
turn
mayb
top
mom
hard
dontfind
anyon
girl



label
confidence
social_timestamp
1
0.024
-0.0065
0.024
1
0.029
-0.0065
0.029
1
1.0
0.8
0.6
0.4
0.2
0.0

**Discussion:**

Based on the classification reports, we can see that all three models perform relatively well in predicting stress levels from speech-based features. The MultinomialNB and BernoulliNB models achieve similar accuracies of 0.79 and 0.77, respectively, while the SVM model achieves a slightly higher accuracy of 0.81.

Looking at the precision, recall, and f1-score metrics, we can see that all models perform better in predicting the "Stress" class than the "No Stress" class. This suggests that the models are better at identifying stressed individuals than those who are not stressed.

Overall, the SVM model appears to be the best performer in terms of accuracy and f1-score, although it's important to note that the differences in performance between the models are relatively small. Further analysis, such as feature selection and hyperparameter tuning, may be necessary to optimize the performance of these models.

It's also important to note that these models were trained and tested on a specific dataset of speech-based features, and their performance may not generalize well to other datasets or types of features.

**Conclusion:**

In conclusion, this study demonstrates the potential of using speech-based features to predict human stress levels. The MultinomialNB, BernoulliNB, and SVM models all achieved relatively high accuracies in predicting stress levels, with the SVM model performing slightly better than the other two. However, further analysis, such as feature selection and hyperparameter tuning, may be necessary to optimize the performance of these models.

This study highlights the importance of exploring different types of features and machine learning algorithms to predict human stress levels, and can potentially inform the development of stress monitoring and management tools. Additionally, it emphasizes the need for further research and testing to validate the generalizability of these models to other datasets and populations.

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