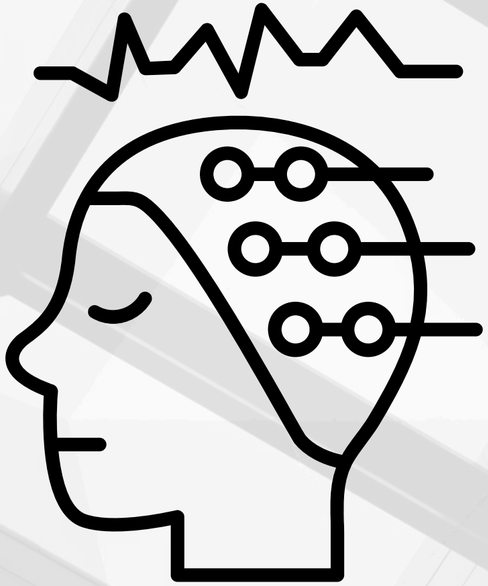

MENTAL STRESS DETECTION

EEG Headset

GROUP 22

Hanoi • Jun. 2024

GROUP MEMBER

GROUP 22

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MENTAL STRESS DETECTION USING EEG HEADSET

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- CNN

Result
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MENTAL STRESS DETECTION USING EEG HEADSET

1. INTRODUCTION

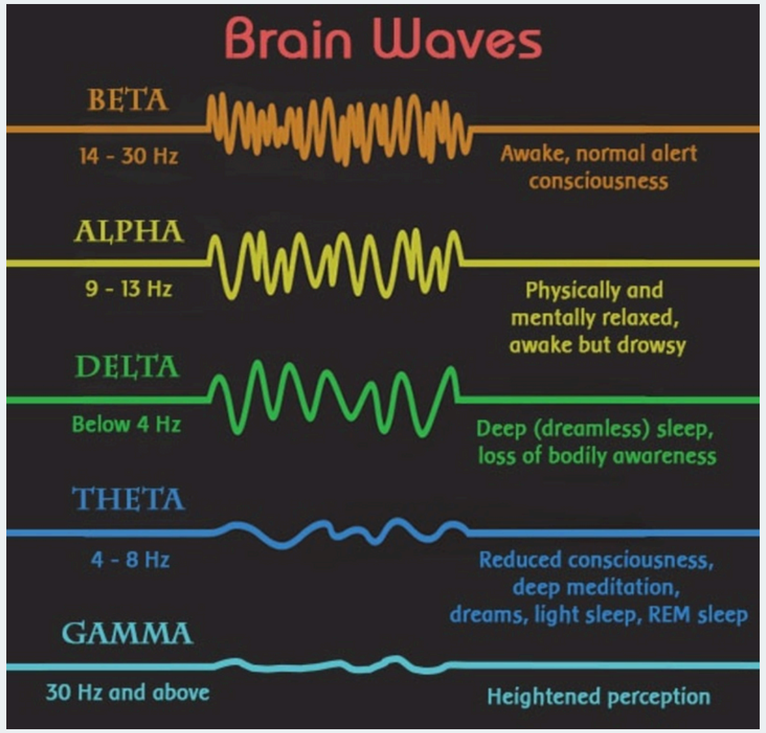
- Stress is stated as a mechanism of the body to respond to a challenge or reaction to mental, emotional, or physical pain.
- Cause dysfunctional behavior, exacerbate hypertension, cardiovascular disease, bowel disease.
- Get forgetfulness, moodiness and loneliness under long stress duration.

Develop an easy accessible, cost-effective, and user-friendly Brain - Computer Interface (BCI) system to detect mental stress state base on EEG signal

2. BACKGROUND

BRAINWAVES AND EEG SIGNAL

- Brainwaves are oscillating electrical voltages generated by nerve cells.
- Brainwaves can be measured through an Electro-EncephaloGraphy (EEG)
- EEG is a test that attaches small electrodes on the scalp to measure electrical activity in the brain.
- EEG signal provides information about time, frequency, phase, and power of brainwaves.
- There are five types of brainwaves, including: alpha, beta, theta, delta, and gamma waves.



2. BACKGROUND

STRESS AND BRAINWAVES

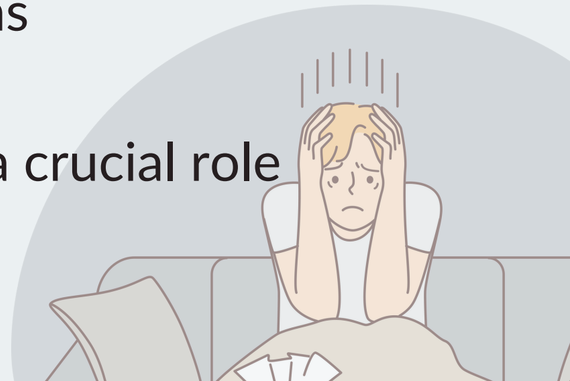
Stress definition

- Stress can be defined as a state of worry or mental tension caused by a difficult situation
- The stress response can be measured from perceptual and physical human responses
- Body under stress releases stress-related hormones to cause hormonal changes in the body

=> Impact the brain and EEG signals

Brainwave changes

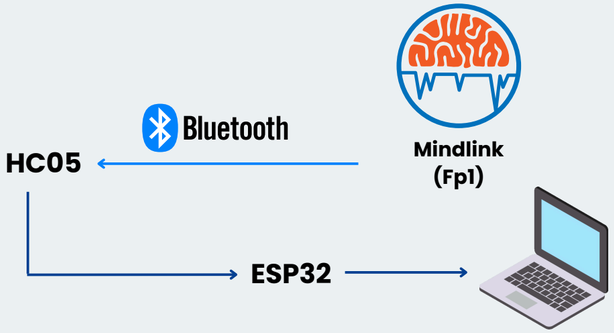
- Stress is positively correlated with beta EEG power
- Left hemisphere is involved in positive emotions,
- Right hemisphere plays a prominent role in negative emotions
- Prefrontal cortex plays a crucial role

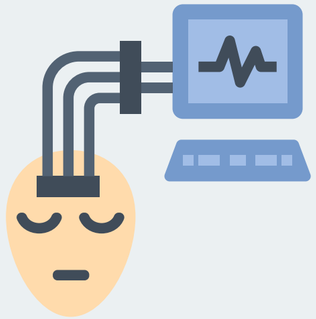


3. DATA ACQUISITION

Collected the EEG data from 5 subjects.
The data collecting process last for 6 minutes
=> 30 minutes EEG signal

The stress was induced in these volunteers by showing stressful/goodmood videos to them, and the EEG signal was then acquired.





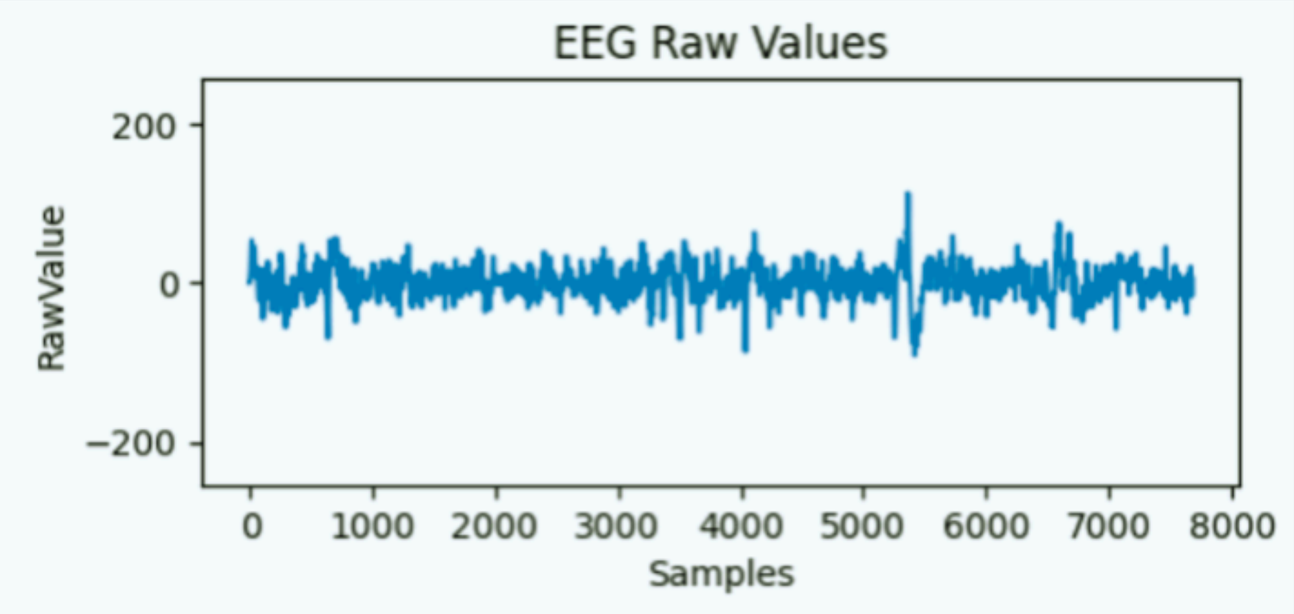
The system was the 3-electrode (Fp1, Fp2, Fpz) Mindlink headband.
Sampling rate is 512Hz. Bandpass filter 0.5Hz - 40Hz

3. DATA ACQUISITION

Music video	Emotional stress state
Billie Eilish, Khalid - lovely	Stressful (Distressing beat and lyrics, sad scenes)
Joji - Glimpse of Us	Stressful (Self destruction scenes, sad melody and lyrics)
Lewis Capaldi - Wish You The Best	Stressful (Scenes of parting, loss of loved ones)

Music video	Emotional stress state
Mark Ronson, Bruno Mars - Uptown Funk	Goodmood (Energetic, vibrant funk, upbeat music)
Maroon 5 - Sugar	Good mood (Happy, marriage scenes; lively and upbeat melody)
Pharrell Williams - Happy	Good mood (Joyful dancing scenes; happy beat and lyric)

3. DATA ACQUISITION



The sliding window will be set for 15s
Overlapping for 14s

4. FEATURE EXTRACTION

TIME DOMAIN

TIME_SERIES_FEATURES:

Variance, RMS, Peak-to-peak Amplitude

Variance:

$$s^2 = \frac{\sum_{i=1}^{n}(x_i - \mu)^2}{N - 1}$$

RMS:

$$RMS = \sqrt{\frac{\sum_{i=1}^{N}(x_i)^2}{N}}$$

Peak-to-Peak:

$$Ptp = |x_{max} - x_{min}|$$

HJORTH_FEATURES:

Hjorth Mobility, Hjorth Complexity

Hjorth_features :

$$Mobility = \sqrt{\frac{var(dx(t))}{var(x(t))}}$$

$$Complexity = \sqrt{\frac{var(dx^2(t))}{var(x(t))}}$$

FRACTAL_FEATURES

Higuchi Fractal Dimension, Katz Fractal Dimension

Katz_fractal

$$FD = \frac{\log N}{\log L}$$

Higuchi_fractal

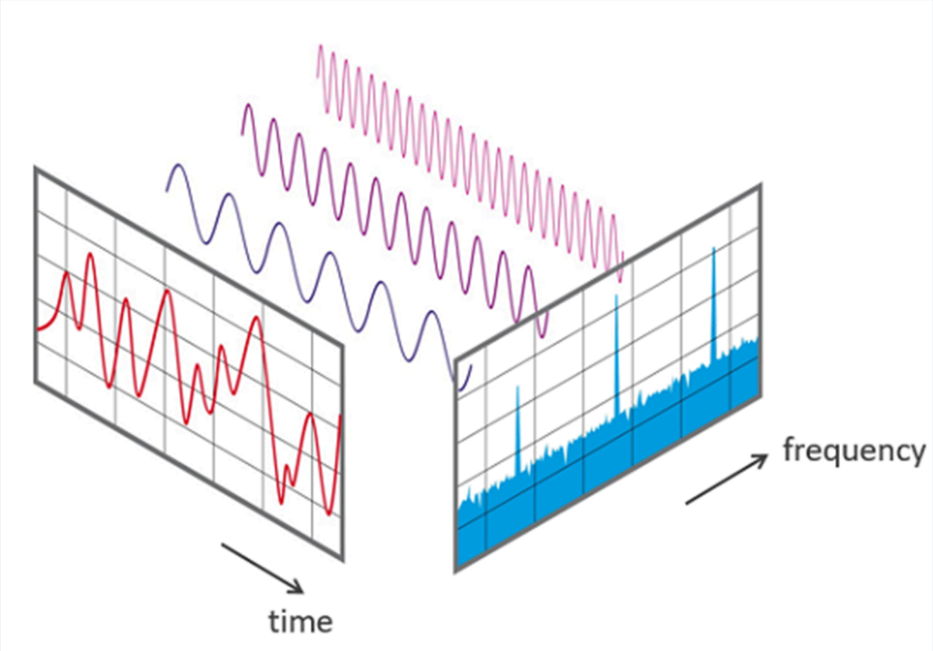
$$FD = \frac{\log lk}{\log k}$$

4. FEATURE EXTRACTION

FREQUENCY DOMAIN

Fast Fourier Transform (FFT):

- Transforms a signal from time-domain to frequency-domain
- Extracts power values of signal by 4 frequency bands: delta, theta, alpha, beta
- Along with ratios of power value between bands -> used as input for models to learn

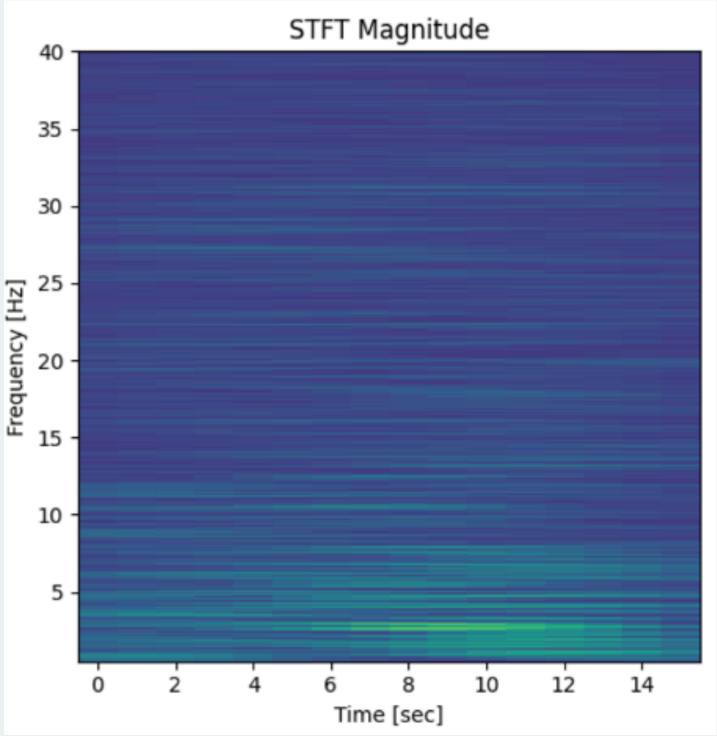


4. FEATURE EXTRACTION

TIME - FREQUENCY DOMAIN

- Time-frequency analysis extract information in both temporal and frequency characteristics of EEG signal.
- Short-Time Fourier Transform (STFT) and Wavelet transforms are the most widely used.
- STFT computes the FFT over short, overlapping segments windows

=> Reveal the time intervals during which specific frequencies are present in the signal.



Spectrogram of STFT

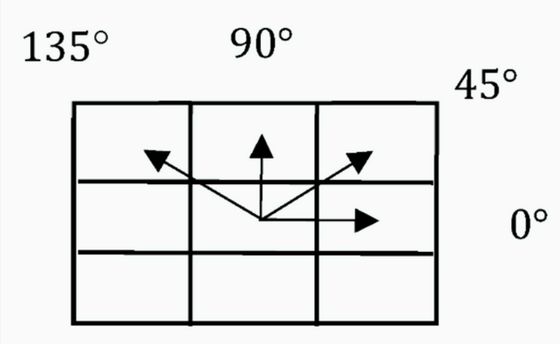
$$I_X(n,k) = \sum_{m=-\infty}^{\infty} x[m]w[n-m]e^{\frac{-j2\pi km}{N}}$$

where x[m] is the signal to be analyzed and N is the frequency sampling factor, frequency ω = 2πk/N.

4. FEATURE EXTRACTION

TIME - FREQUENCY DOMAIN

- Gray-Level Co-occurrence Matrix (GLCM) is used in texture and feature analysis from gray-level images.
- The GLCM cosider the spatial relationship between pixels, in a specific direction (0°, 45°, 90°, or 135°) and distance.
- The GLCM can be used with STFT matrix to extract feature from EEG signal

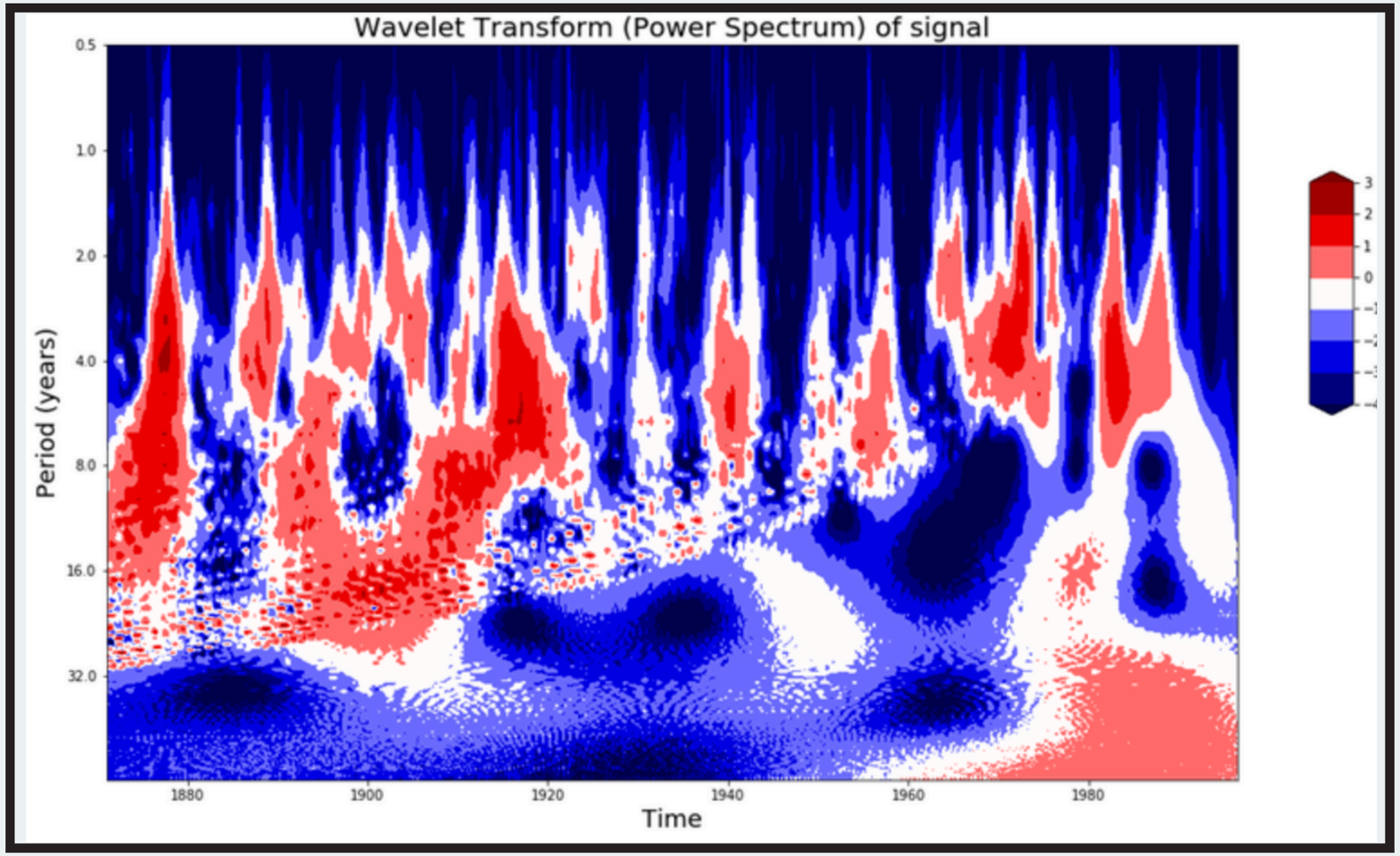


Feature name	Equation
Contrast	$\sum_{i,j} \lvert i-j \rvert^2 p(i,j)$
Correlation	$\sum_{i,j} \frac{(i-\mu_i)(i-\mu_j)p(i,j)}{\sigma_i \sigma_j}$
Energy	$\sum_{i,j} (p(i,j))^2$
Homogeneity	$\sum_{i,j} \frac{p(i,j)}{1+\lvert i-j \rvert}$
Entropy	$\sum_{i,j} p(i,j) log_2 p(i,j)$

Feature contains contrast, correlation, energy, homogeneity, and entropy.

Wavelet Transform

Time-frequency Feature Extraction



Wavelet Spectrogram

FT Uncertainty Principle

$$\left(\int_{-\infty}^{\infty} t^2 |f(t)|^2 dt\right) \cdot \left(\int_{-\infty}^{\infty} u^2 |\hat{f}(u)|^2 du\right) \geq \frac{1}{16\pi^2}$$

How “spread out” the signal is **in time.**

How “spread out” the signal is **in frequency.**

Wavelets

- In French, it means “small waves”.
- Family of functions satisfying the two conditions:

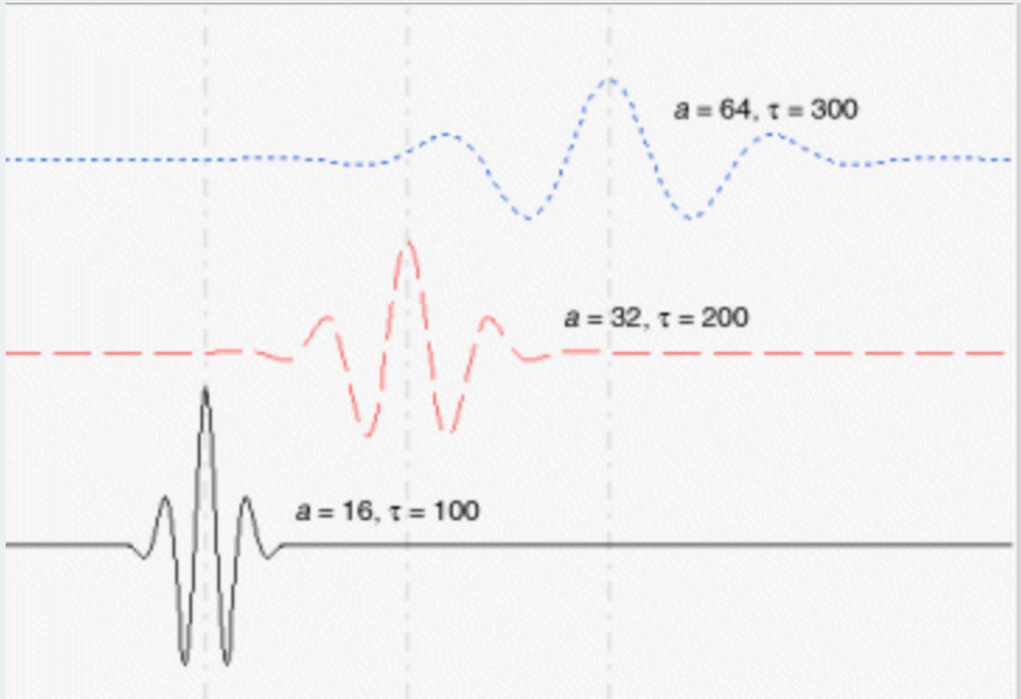
ZERO MEAN

$$\int_{-\infty}^{+\infty} \Psi(t)dt = 0$$

FINITE ENERGY

$$\int_{-\infty}^{+\infty} |\Psi(t)|^2 dt < \infty$$

Wavelet Transform



Morlet Wavelets

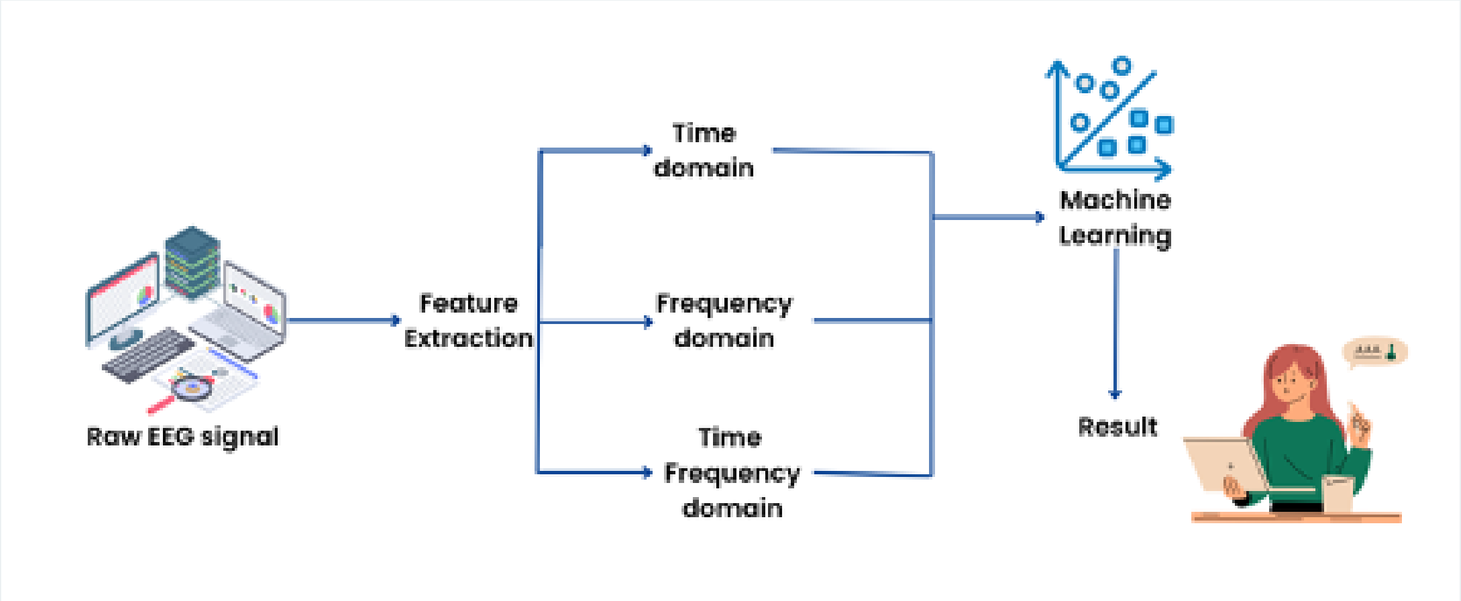
Continuous Wavelet Transform (CWT)

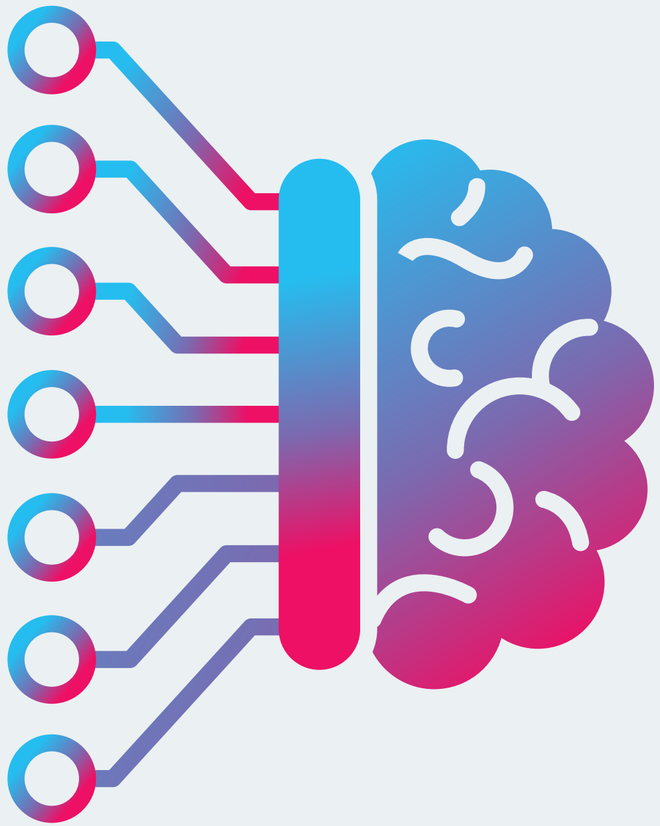
$$T(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\, \psi^* \frac{(t-b)}{a} dt$$

a: Scale (or dilation) parameter
b: Location of wavelet
Ψ: Wavelet function
x: Signal

Continuous Wavelet Transform formula

5. AI MODEL


Raw EEG signal
Feature Extraction
Time domain
Frequency domain
Time Frequency domain
Machine Learning
Result



SUPPORT VECTOR MACHINE

SVM with Frequency domain

GOOD PERFORMANCE ON HIGH DIMENSIONAL PROBLEMS

Preprocess of EEG signal from time-domain into frequency-domain and group into different bands

HYPERPARAMETERS

- Penalty constant C: 0.1, 1, 10, 100?
- Kernel function: linear, RBF, polynomial?

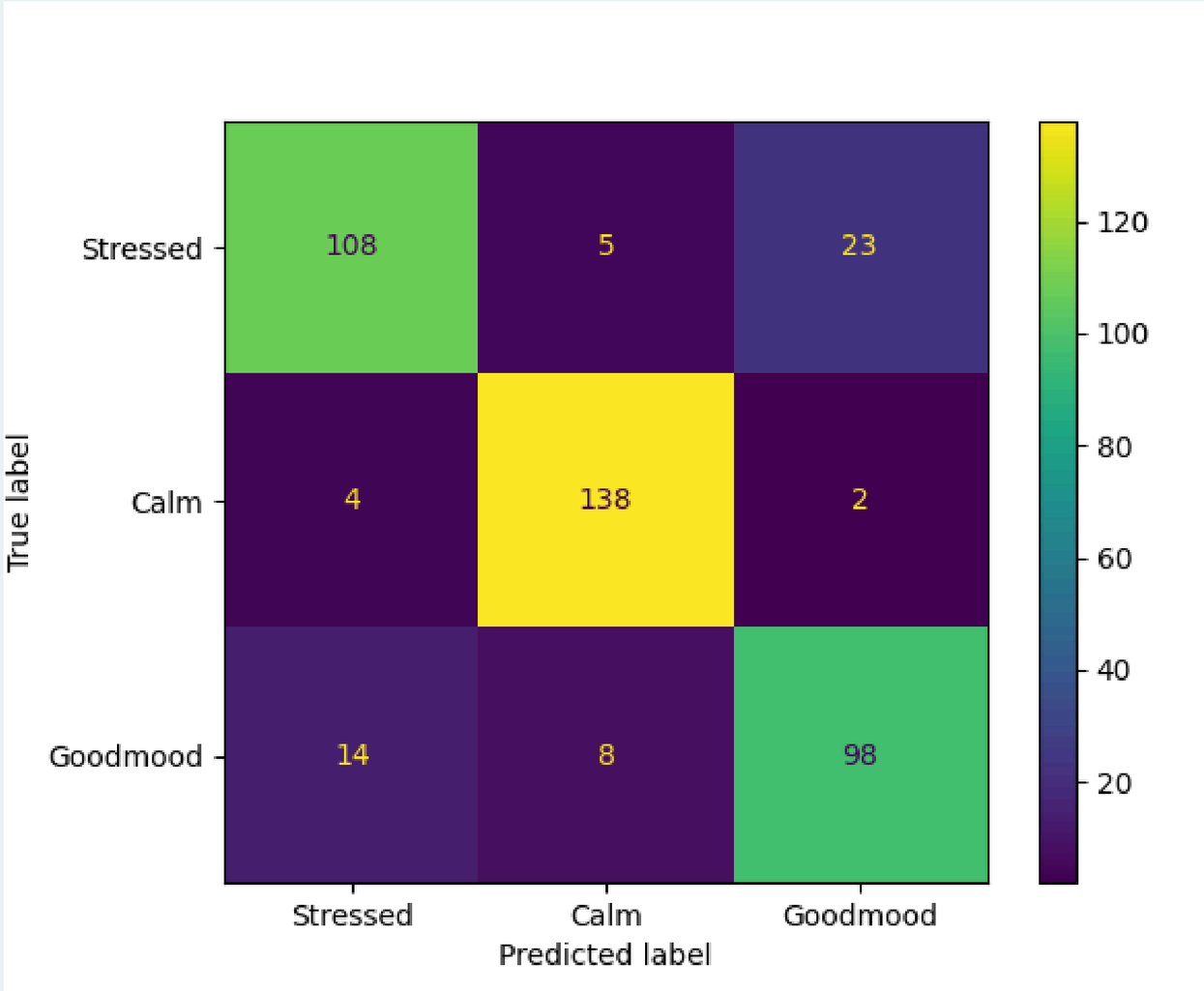
EXISTING STUDIES

- Quantifying 2 levels of stress: 75% - 90%
- More levels -> less efficient

SVM Accuracy

Using C=100, RBF kernel function:

- For 1 hold-out test with 20% of dataset used for testing:
  - Train accuracy: 90%
  - Test accuracy: 86.1%
- 10-fold cross-validation: 88.8%
- Slight confusion between stressed and good-mood states: ~0.75 on F1-score



SUPPORT VECTOR MACHINE

SVM with Time - Frequency domain

FEATURE EXTRACTION

Raw EEG is transformed into a STFT matrix concludes both time - frequency information. GLCM technique is applied to extract features

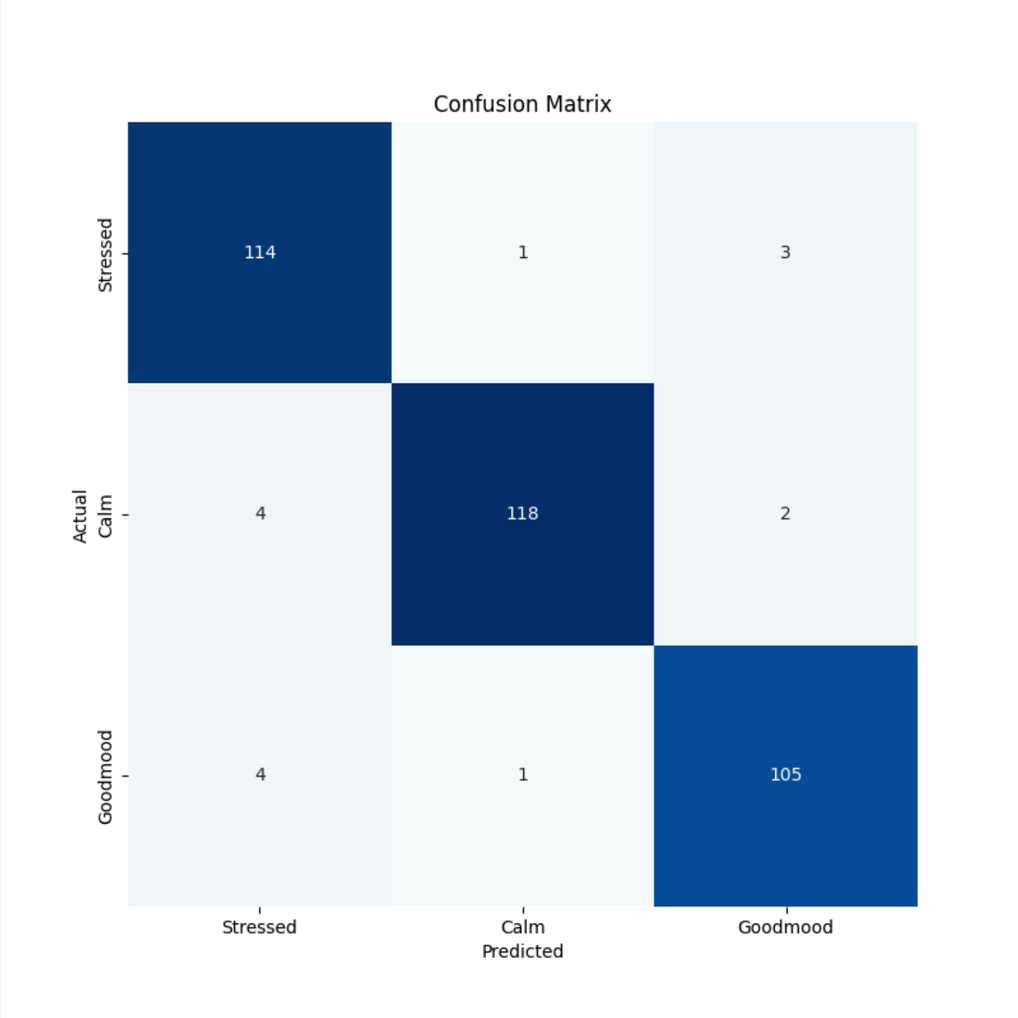
HYPERPARAMETERS

- Penalty constant C: 0.1, 1, 10, 100
- Kernel function: linear, RBF, polynomial
- gamma: 'scale', 'auto'

SVM Accuracy

Using C=100, RBF kernel, gamma=1:

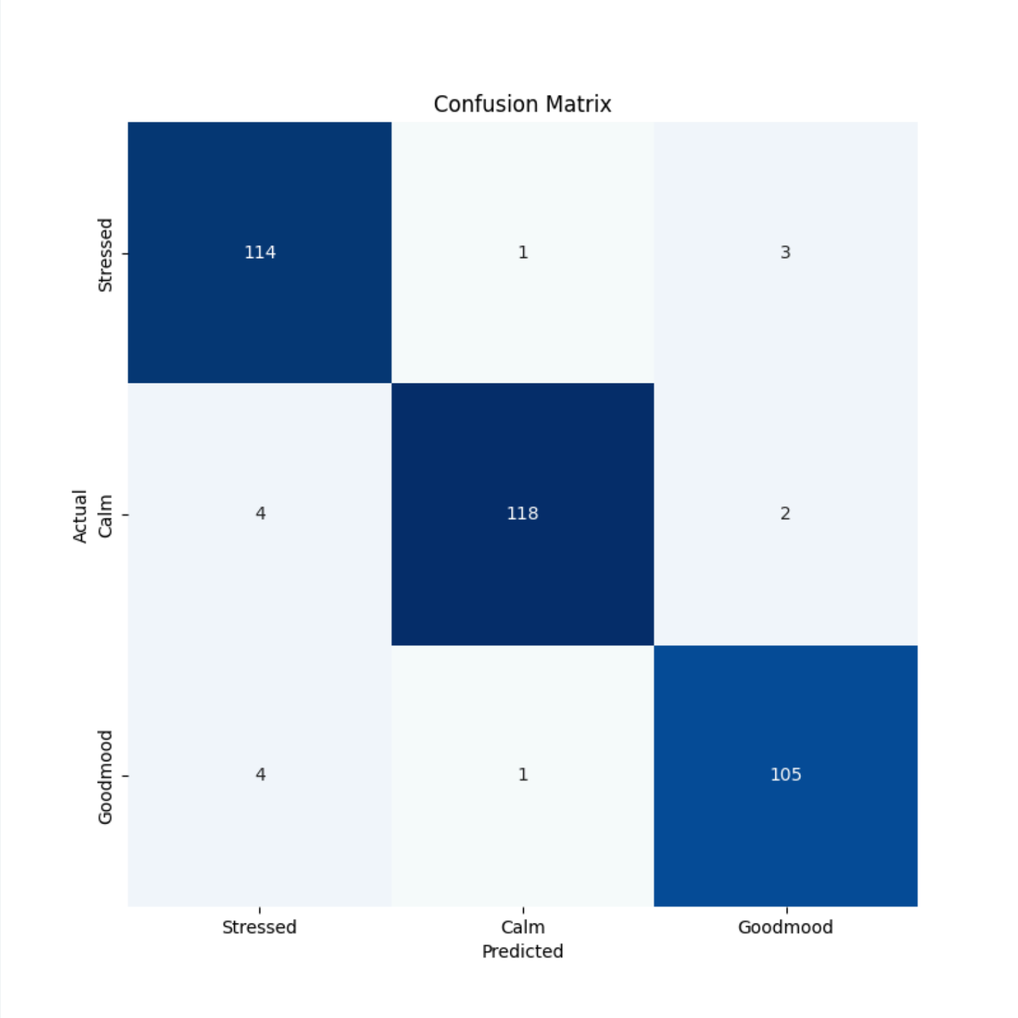
- For 1 hold-out test with 20% of dataset used for testing:
  - Train accuracy: 100%
  - Test accuracy: 95.5%
- 10-fold cross-validation: 94.3%



SVM Accuracy

Using C=100, RBF kernel, gamma=1:

	precision	recall	f1-score	support
Stressed	0.95	0.95	0.95	110
Calm	0.93	0.96	0.95	118
Good mood	0.98	0.95	0.97	124
accuracy			0.95	352
macro avg	0.95	0.95	0.95	352
weighted avg	0.96	0.95	0.95	352



BOOSTING ALGORITHMS: GRADIENT BOOSTING

ADABOOST?

Prioritizes mislabeled datapoints; potential artifacts or noises in dataset
-> Poor performance

ENSEMBLE OF WEAK LEARNERS

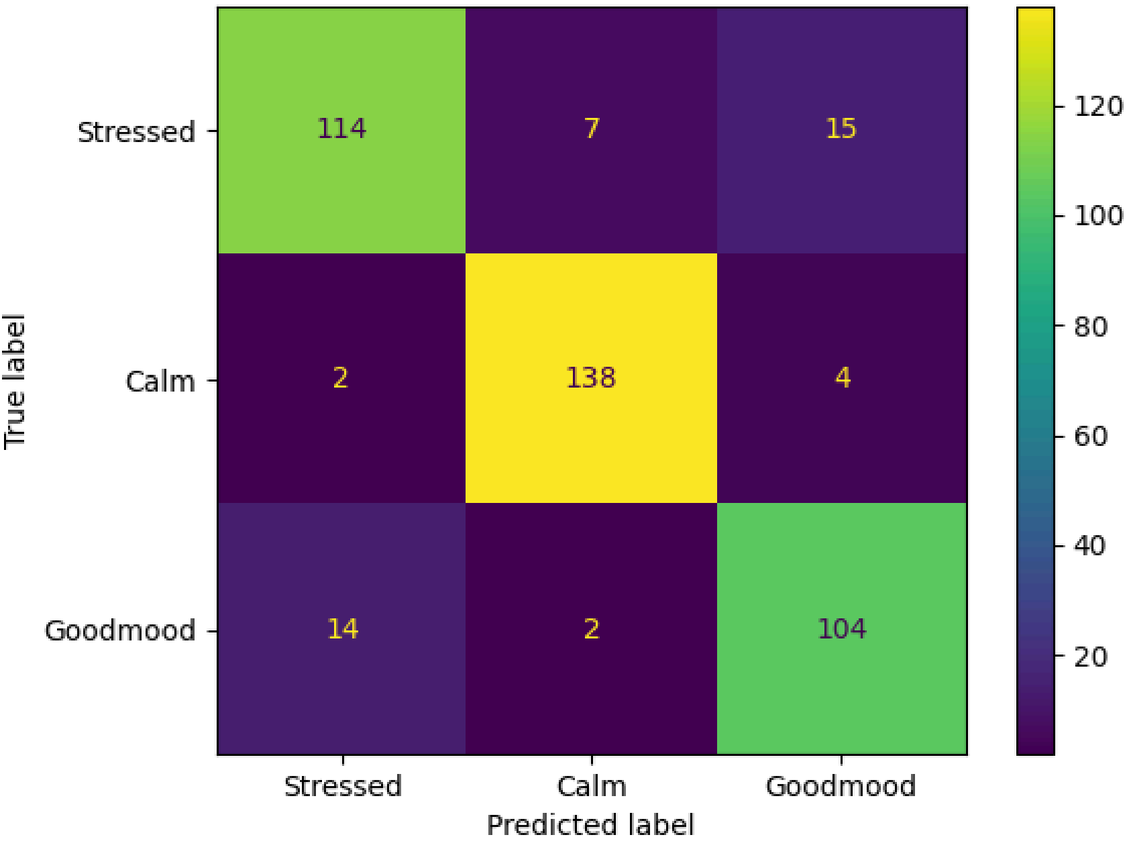
- Decision Trees: quick learning with low terminal depths
- How deep should one tree be grown?

LEARNING PROCESS

- Output of previous estimator -> input of next one
- Each step: minimize error using Gradient Descent

MODEL SELECTION

- Num. of weak estimators
- Learning rate: significance of each estimator in the ensembled model



With 200 trees, depth of 7 each

- GB can perfectly fit into a training set; still perform well on new data: 90.5% accuracy
- 90.25% accuracy on average with K-Fold
- All classes have >0.85 F1 score -> good generalization

MULTILAYER PERCEPTRON

AN ARTIFICIAL NEURAL NETWORK

- Ability to solve non-linear problems
- Many studies acquired good results with MLP

MODEL SELECTION

- Activation function
- Size: number of layers & perceptrons per layer
- Unsuitable activation function -> underfit
- Too many neurons -> overfit

=> Require careful selection

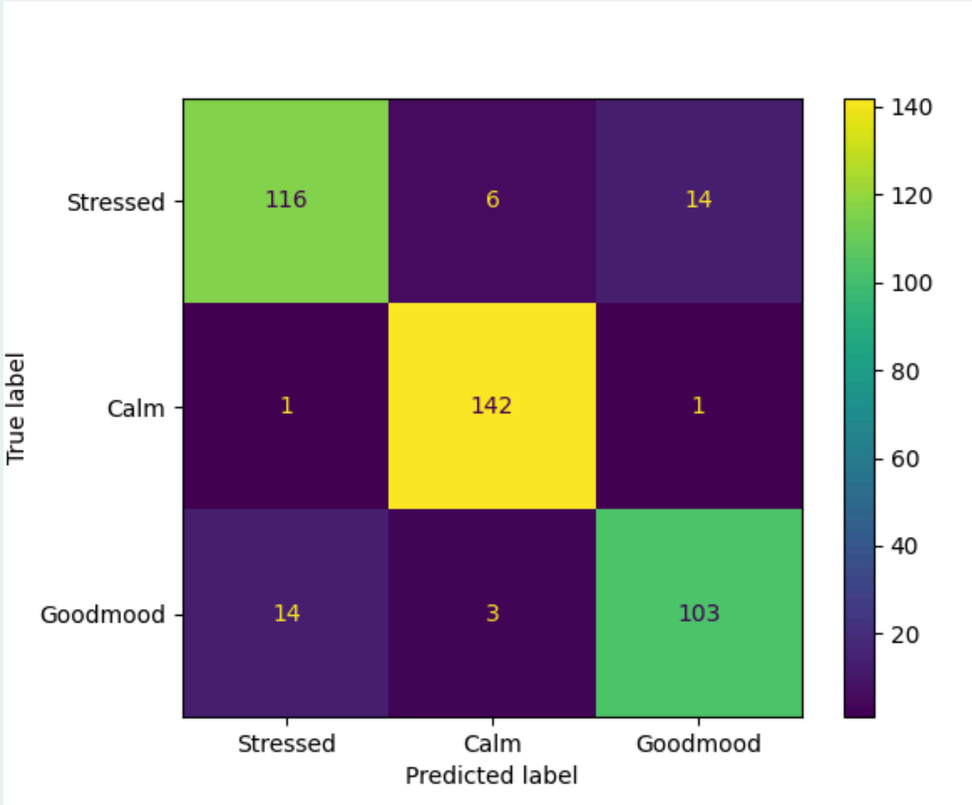
Using Grid Search for evaluation

ACTIVATION FUNCTION

- Sigmoid & hyperbolic tangent: <40% accuracy
- Identity: ~80% -> more desirable
- ReLU: ~90% -> selected for model; provide flexibility in dealing with outliers

NETWORK SIZE

- Multiple structures considered: 1 x 100, 2 x 100, 3 x 75, ... (layers x neurons per layer)
- Too many layers lead to MLP not converging in training process -> perform worse
- Combined with ReLU: 5 x 50 perceptrons gave 92.1% accuracy with K-Fold

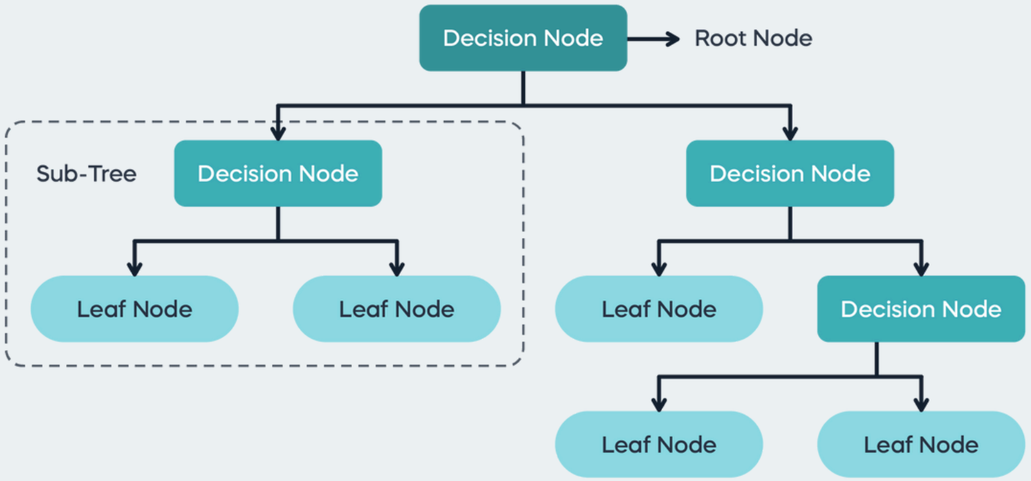


DECISION TREE

- Decision Trees are tree-like models

- Internal nodes are feature tests
- Branches are decision rules
- Leaf nodes are the final predicted classes.

- Instance is traversed through the tree from the root node to a leaf node, following the feature tests at each internal node.



DECISION TREE

FEATURE EXTRACTION

Raw EEG is transformed into a STFT matrix concludes both time - frequency information. GLCM technique is applied to extract features

HYPERPARAMETERS

- Criterion: gini, entropy
- max_depth: None, 7, 10, 20, 30
- min_samples_split: 2, 5 ,10

RESULT

HYPERPARAMETERS

- Criterion: entropy
- max_depth: 7
- min_samples_split: 5

For 1 hold-out test with 20% of dataset used for testing:

- Train accuracy: 97.8%
- Test accuracy: 88.1%

10-fold cross-validation: 88.3%

	precision	recall	f1-score	support
Stressed	0.86	0.86	0.85	110
Calm	0.82	0.87	0.85	118
Good mood	0.96	0.92	0.94	124
accuracy			0.88	352
macro avg	0.88	0.88	0.88	352
weighted avg	0.88	0.88	0.88	352

RESULT

HYPERPARAMETERS

- Criterion: entropy
- max_depth: 7
- min_samples_split: 5

For 1 hold-out test with 20% of dataset used for testing:

- Train accuracy: 97.8%
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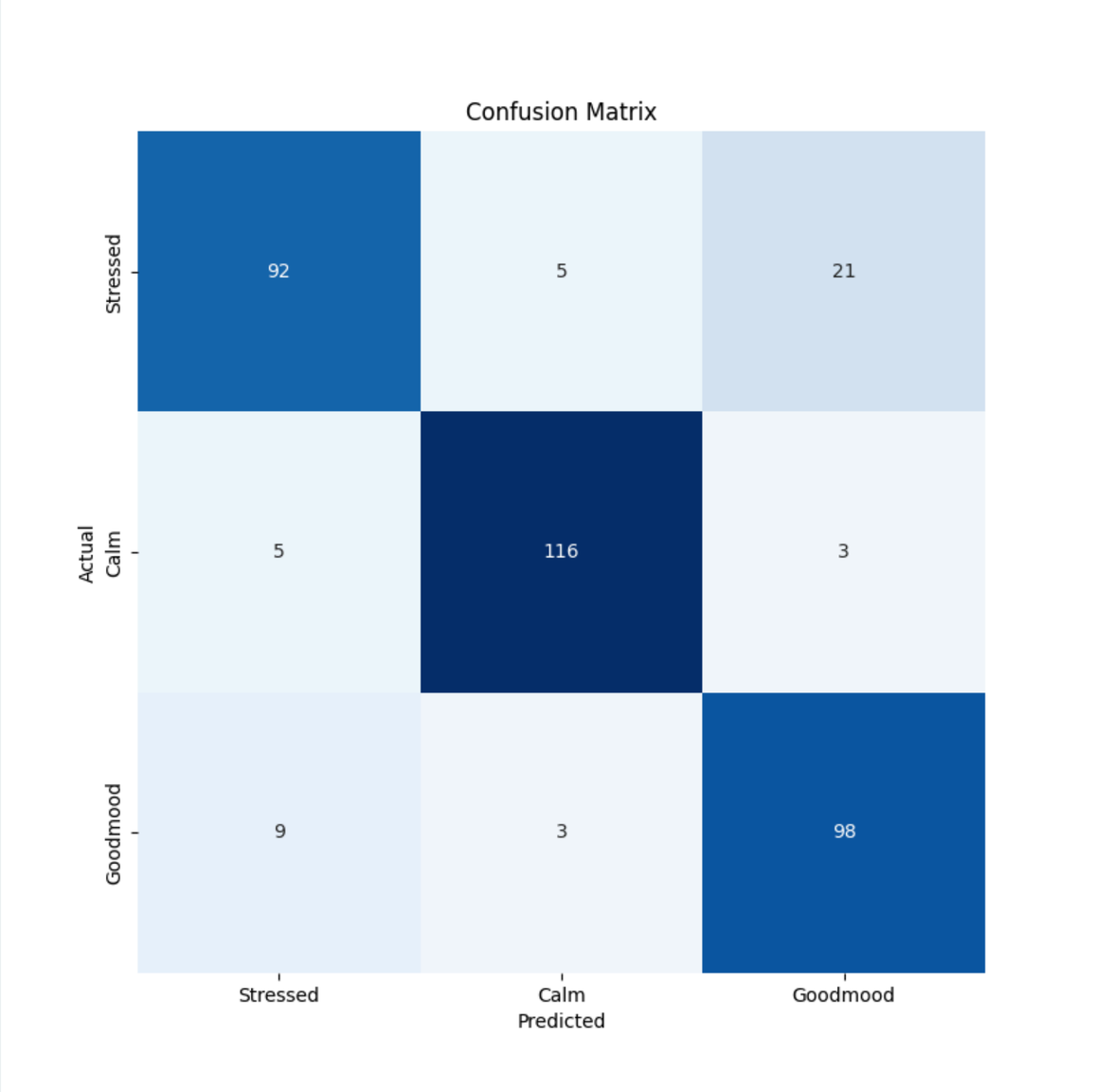
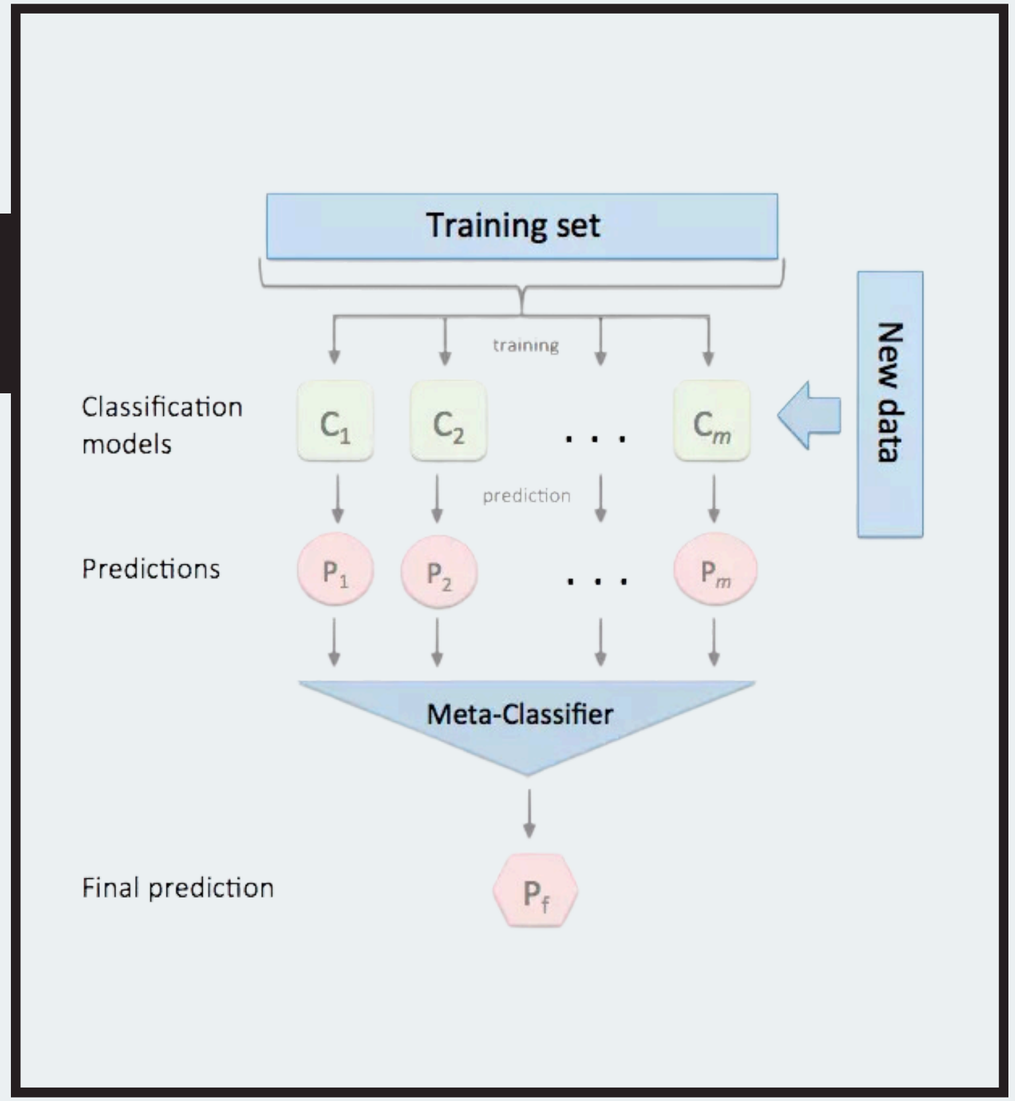
10-fold cross-validation: 88.3%





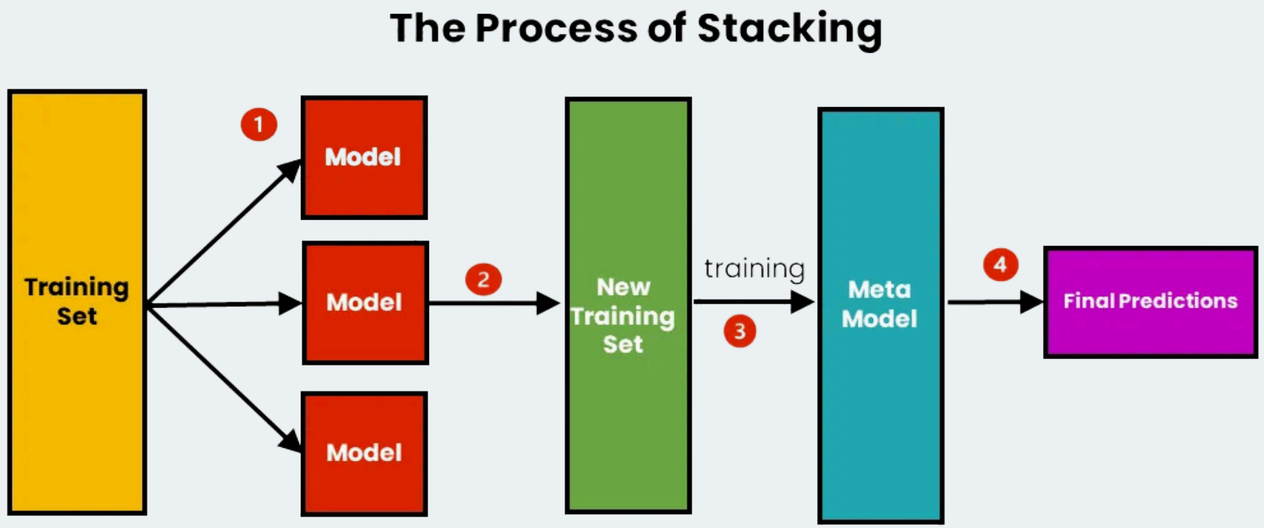
ENSEMBLE LEARNING

Leveraging Machine Learning for Enhanced Accuracy

ENSEMBLE LEARNING | STACKING

Combines predictions of multiple models to improve performance.

Model Choice: Logistic Regression with L2 regularization (Ridge)
Reason: Balances complexity and interpretability, prevents overfitting
L2 Regularization: Adds penalty proportional to the sum of squared coefficients



BASE LEARNERS SELECTION

SUPPORT VECTOR MACHINE (SVM)

- Effective in high-dimensional spaces
- Uses RBF kernel for complex boundaries

RANDOM FOREST (RF)

- Ensemble of decision trees
- Mitigates overfitting

GRADIENT BOOSTING (GB)

- Sequential error correction
- Handles complex interactions

HYPERPARAMETER TUNING

GRIDSEARCHCV

SUPPORT VECTOR MACHINE (SVM)

- C: 0.1
- gamma: scale
- kernel: rbf

RANDOM FOREST (RF)

- n_estimators: 100
- max_depth: 10
- min_samples_split: 10

GRADIENT BOOSTING (GB)

- n_estimators: 100
- learning_rate: 0.01
- max_depth: 3

Stacking Ensemble | Construction

BASE MODELS TRAINING

Trained on the training data

- Support Vector Machine (SVM)
- Random Forest (RF)
- Gradient Boosting (GB)

META-MODEL TRAINING

Predictions from base models used as features

- Logistic Regression

VALIDATION

Stratified K-fold cross-validation (10 folds)

METRICS

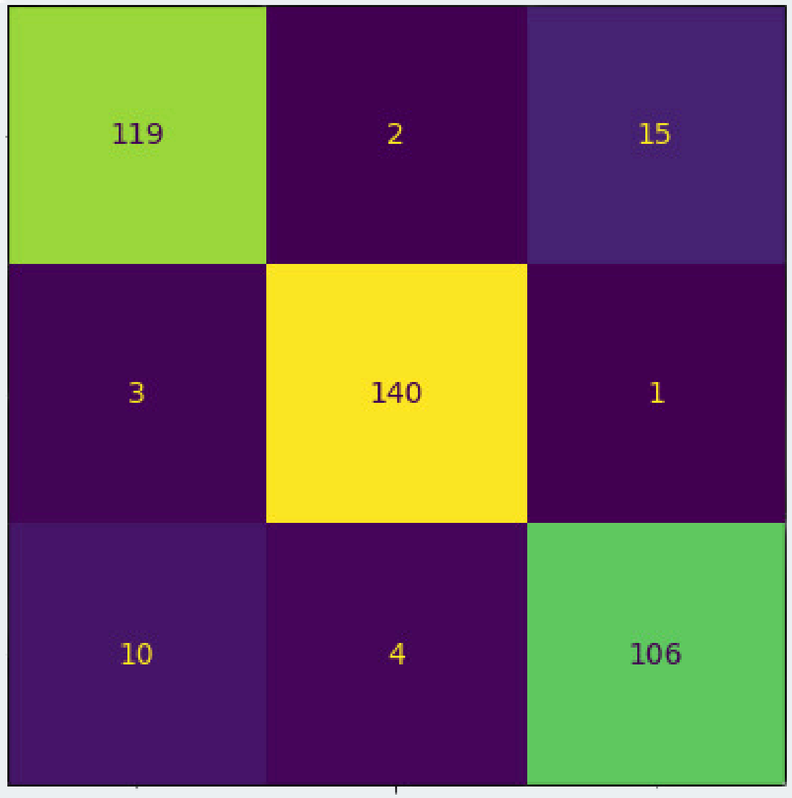
Accuracy, precision, recall, F1-score, and confusion matrices

Stacking Ensemble | Result

	precision	recall	f1-score	support
Stressed	0.90	0.88	0.89	136
Calm	0.96	0.97	0.97	144
Good mood	0.87	0.88	0.88	120
accuracy			0.91	400
macro avg	0.91	0.91	0.91	400
weighted avg	0.91	0.91	0.91	400

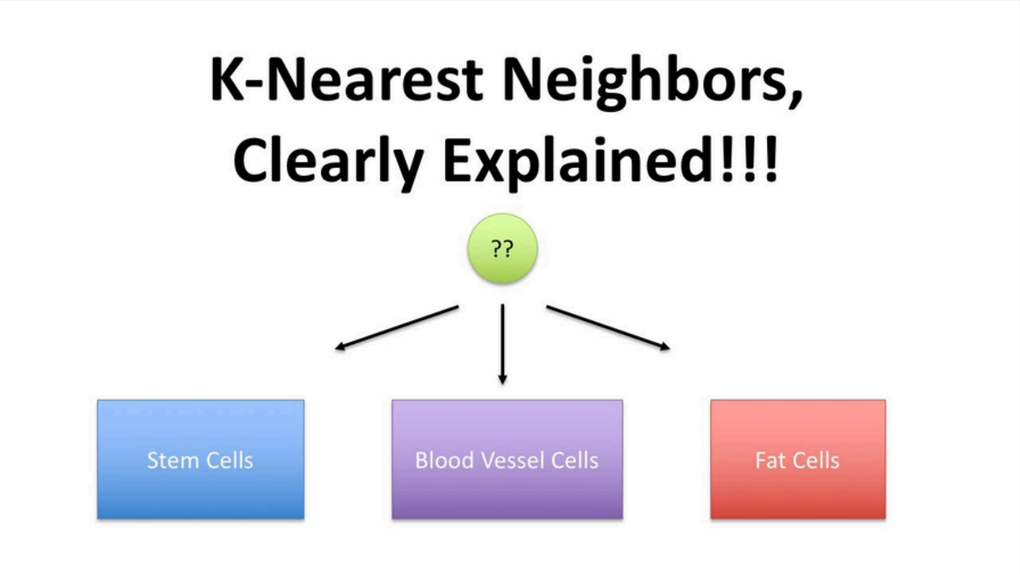
Train accuracy: 0.996875

Test accuracy: 0.9125



K-NEAREST NEIGHBOUR:

SUPERVISED-LEARNING ALGORITHM



K-NEAREST NEIGHBOUR

KNN with Time domain

PARAMETERS

KNN parameters

- leaf_size = 30
- n_neighbors = 5
- p = 2
- weights = uniform

VALIDATION

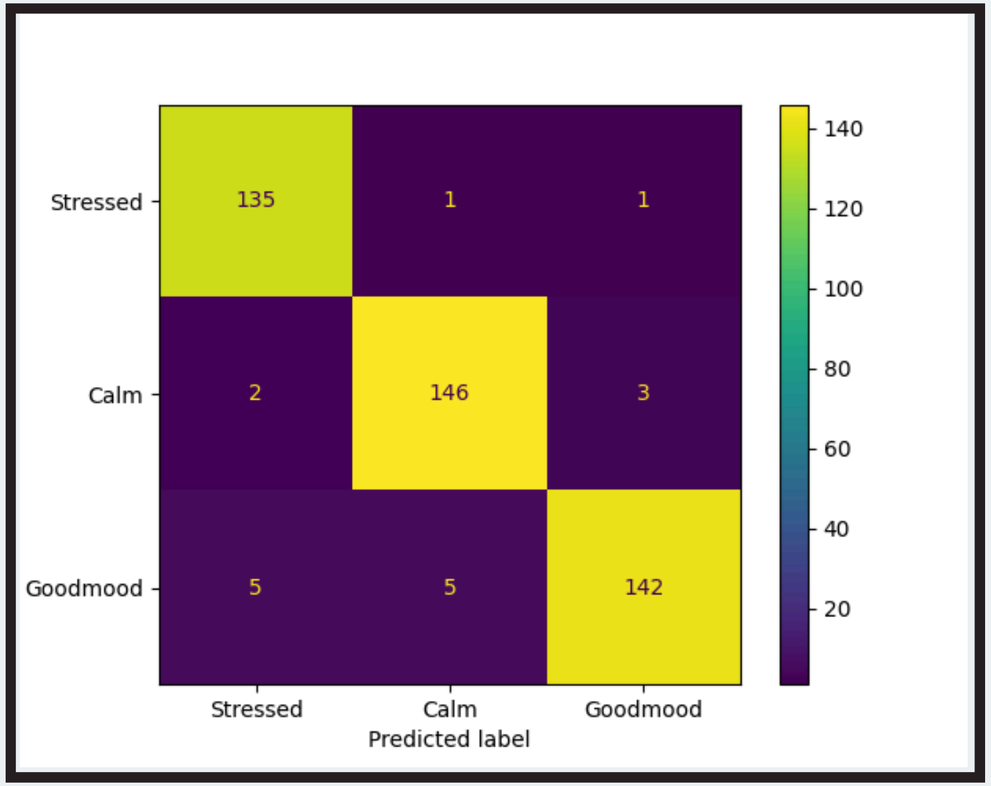
Stratified K-fold cross-validation (10 folds)

METRICS

Accuracy, precision, recall, F1-score, and minkowski matrices

KNN RESULT

	precision	recall	f1-score	support
0	0.97	0.94	0.96	152
1	0.96	0.99	0.97	137
2	0.96	0.97	0.96	151
accuracy			0.96	440
macro avg	0.96	0.96	0.96	440
weighted avg	0.96	0.96	0.96	440



Presentations are communication tools that can be used as lectures.

K-NEAREST NEIGHBOUR

KNN with Time - Frequency domain

FEATURE EXTRACTION

Raw EEG is transformed into a STFT matrix concludes both time - frequency information. GLCM technique is applied to extract features

HYPERPARAMETERS

- n_neighbors = 3, 5, 7, 9
- weights = uniform, distance
- metric = euclidean, manhattan

VALIDATION

- K-fold cross-validation (10 folds)
- Metric: Accuracy, precision, recall, F1-score, and minkowski matrices

KNN RESULT

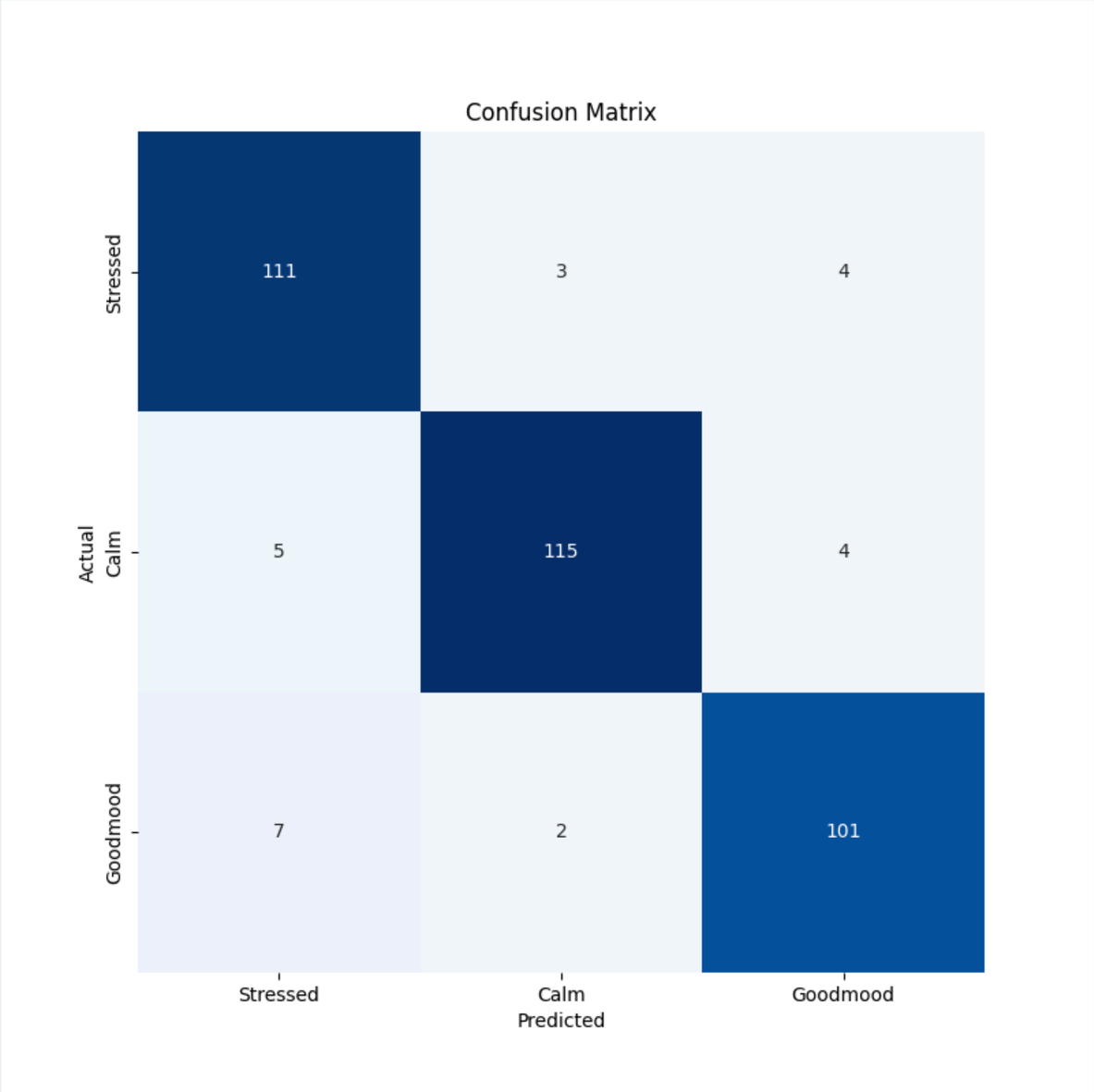
PARAMETERS

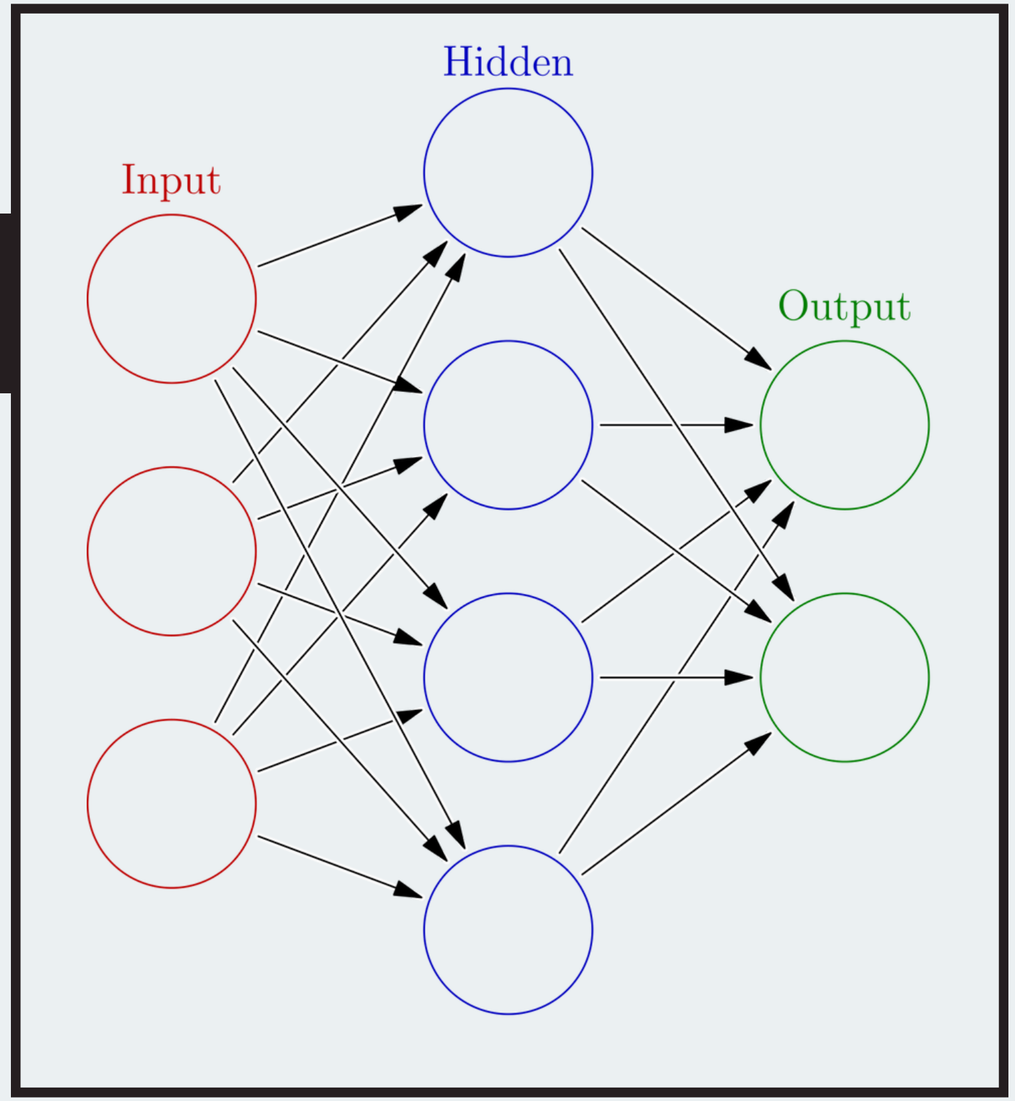
KNN parameters

- n_neighbors = 7
- weights = distance
- metric = manhattan

RESULT

	precision	recall	f1-score	support
NEGATIVE	0.89	0.93	0.91	110
NEUTRAL	0.90	0.91	0.90	118
POSITIVE	0.96	0.92	0.94	124
accuracy			0.92	352
macro avg	0.92	0.92	0.92	352
weighted avg	0.92	0.92	0.92	352





ARTIFICIAL NEURAL NETWORK

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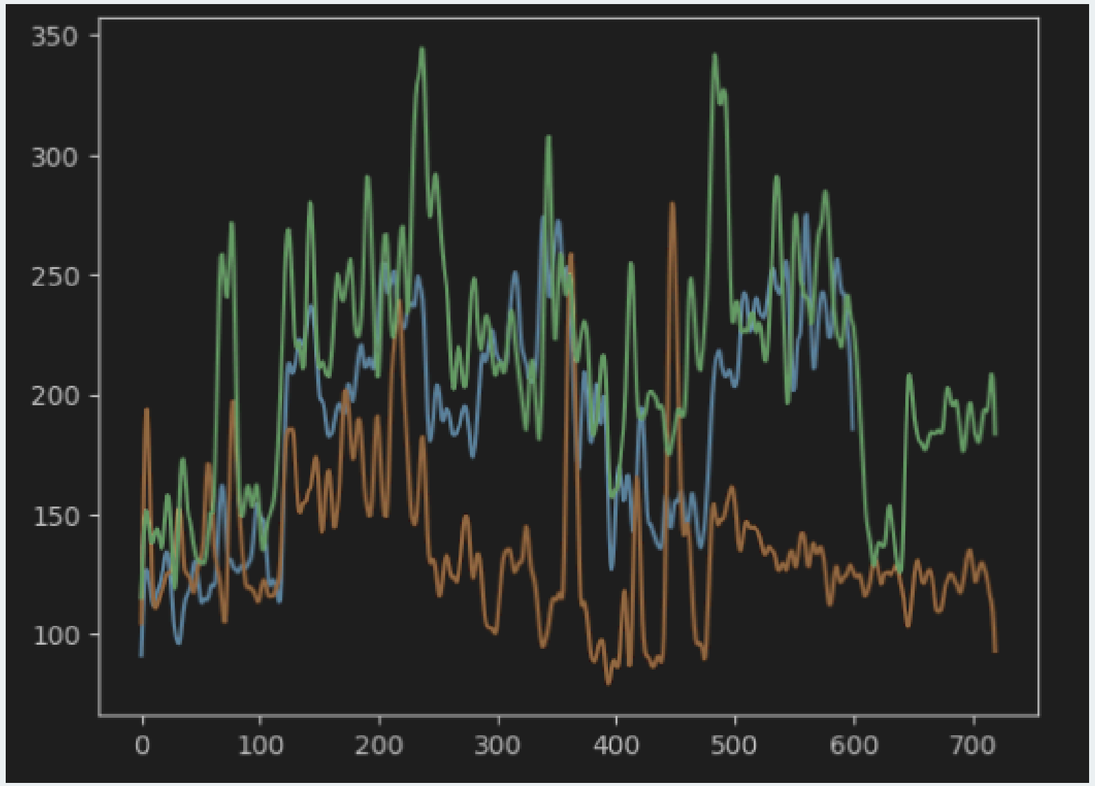
REASON TO CHOOSE

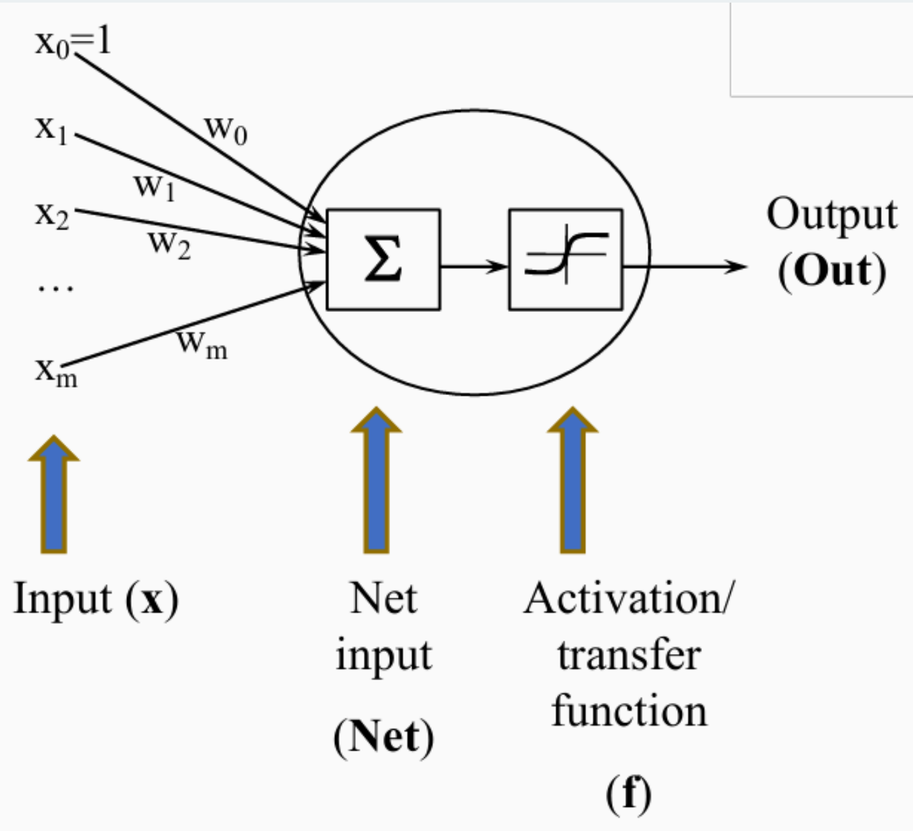
Mean and Variance change over times

- Non-linear
- Non-stationary

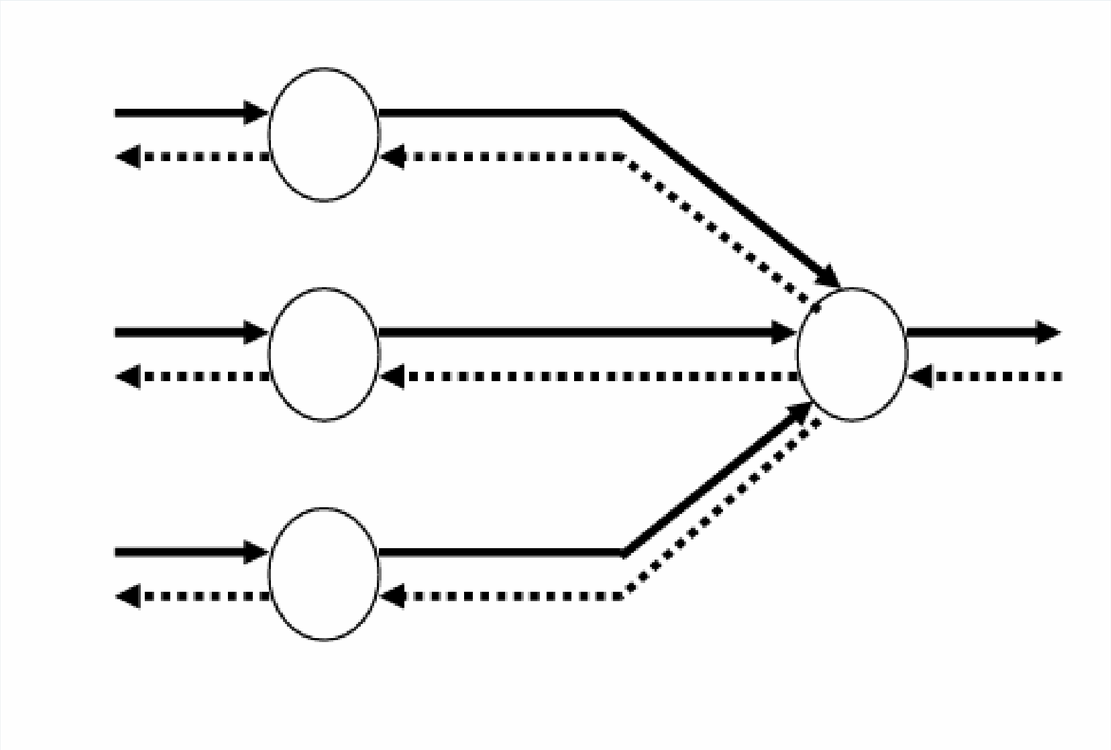


Compare beta signal in 720 seconds
Green line: Goodmood
Orange line: Calm
Blue line: Stressed

FEED FORWARD



BACKPROPAGATION



ANN DATA PREPROCESSING

FEATURE EXTRACTION

Raw EEG is transformed into a STFT matrix concludes time-frequency information.
GLCM technique is applied to extract features

INTEGER ENCODING

- Stressed=0, Calm=1, Goodmood=2
- Maintaining sentiment relationships

LAYER CHOICES

```
weight_decay = 0.001
model = Sequential()
model.add(Dense(64, activation='relu', input_shape=(30, 4),
                kernel_regularizer=regularizers.l2(weight_decay)))
model.add(Flatten())
model.add(Dense(3, activation='softmax'))
```

- Input layer: (batch_size, window_size=30, brainwave_num=4)
- Hidden layer 1: Dense layer with L2 regularization
- Hidden layer 2: Flatten
- Output layer: three categories using softmax activation

ANN RESULT

PARAMETERS

Artificial Intelligence

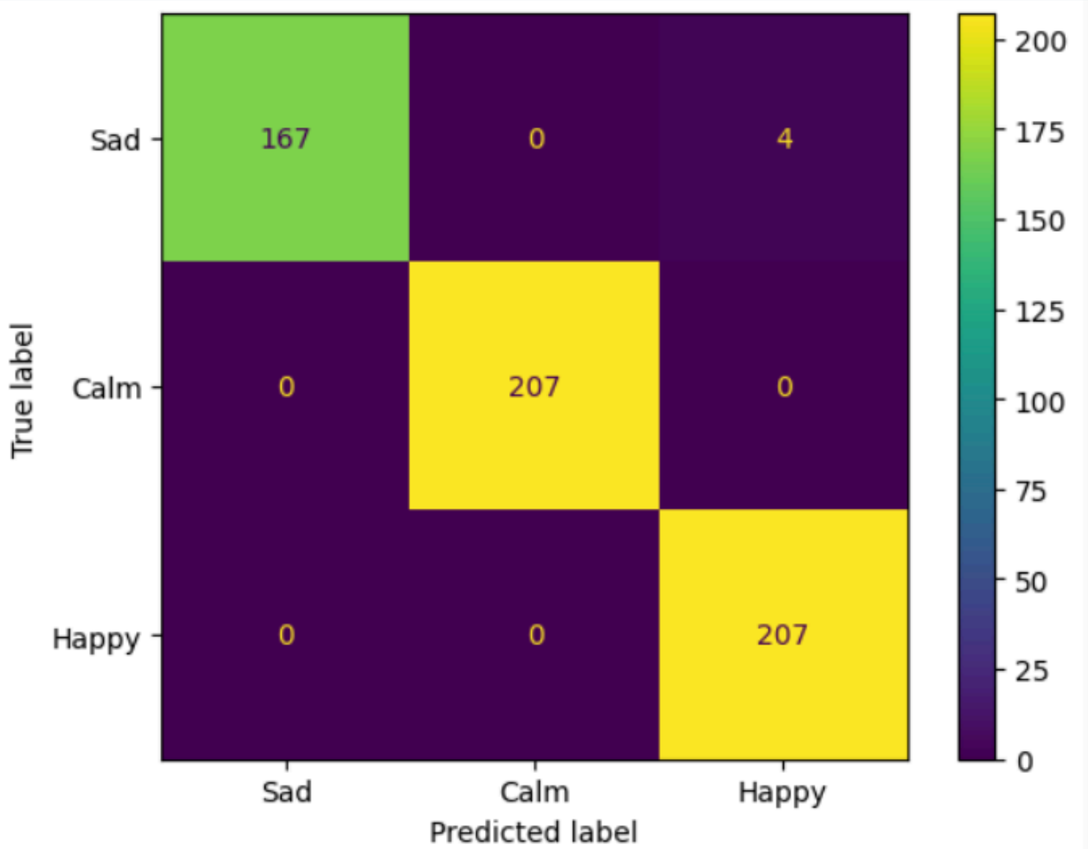
- Optimizer: Adam
- Loss: Categorical Cross Entropy
- Batch size: 32

RESULT

	precision	recall	f1-score	support
0	1.00	0.98	0.99	171
1	1.00	1.00	1.00	207
2	0.98	1.00	0.99	207
accuracy			0.99	585
macro avg	0.99	0.99	0.99	585
weighted avg	0.99	0.99	0.99	585

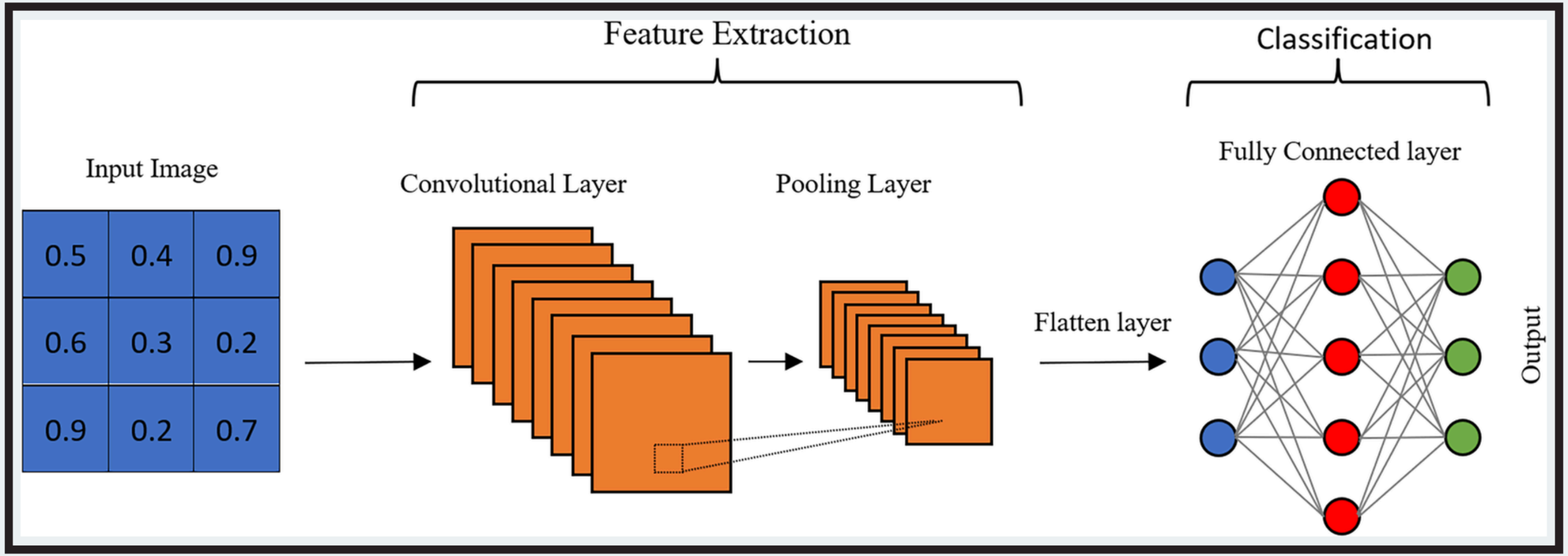
Train accuracy: 1.00

Test accuracy: 0.99



Convolutional Neural Network

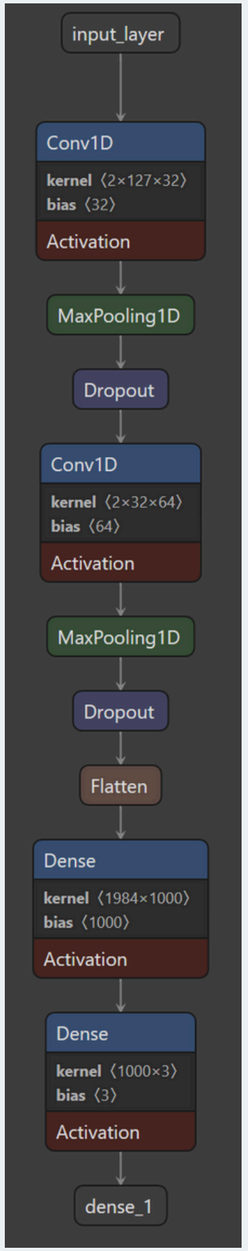
With the application of Continuous Wavelet Transform (CWT)



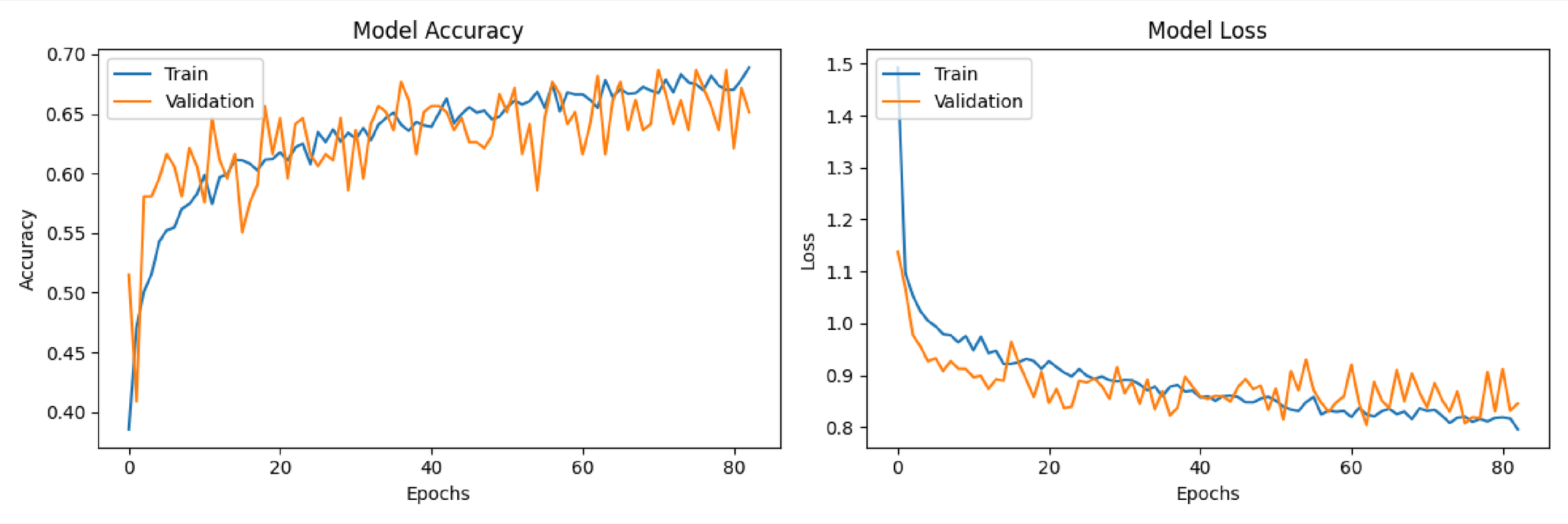
CNN example

Layers

- 2 Convolutional Layers + MaxPooling + Dropout
- 2 Dense Layers + L2 Regularizations + Softmax



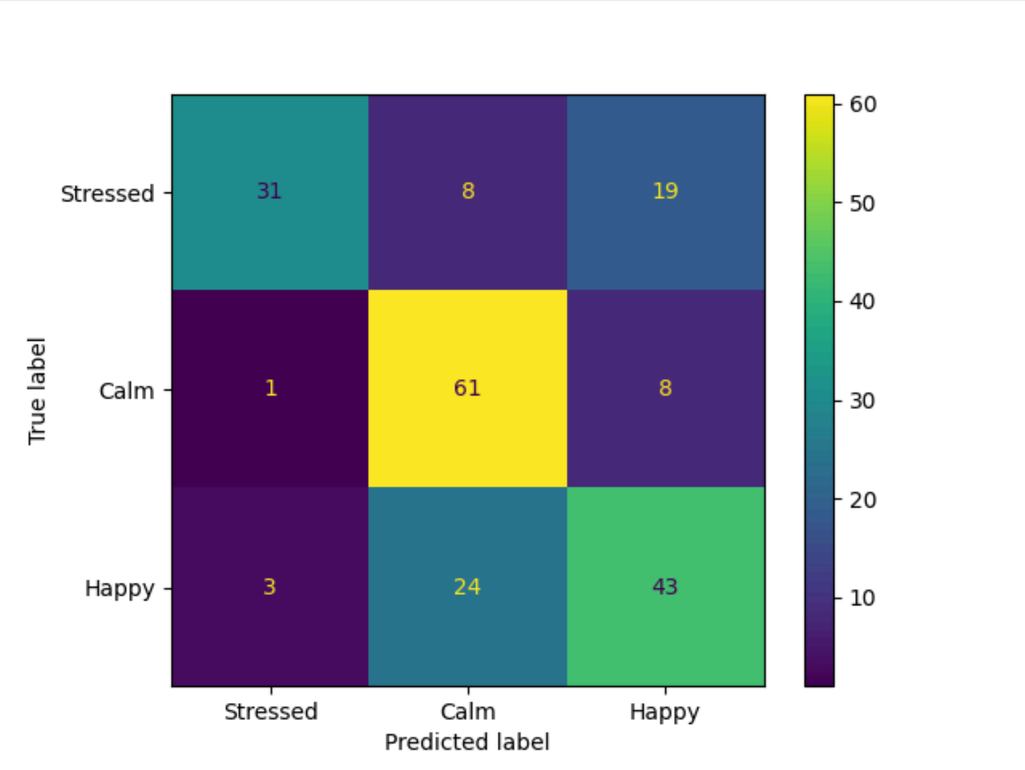
Convolutional Neural Network | Result



Convolutional Neural Network | Result

	precision	recall	f1-score	support
Stressed	0.89	0.53	0.67	58
Calm	0.66	0.87	0.75	70
Good mood	0.61	0.61	0.61	70
accuracy			0.68	198
macro avg	0.72	0.67	0.68	198
weighted avg	0.71	0.68	0.68	198

Train accuracy: 0.702368
Test accuracy: 0.681818



MODEL INSIGHTS

- Fluctuations in both **validation accuracy and loss**
- **Low** accuracy and **high** loss in both the training and validation data.

POSSIBLE IMPROVEMENT

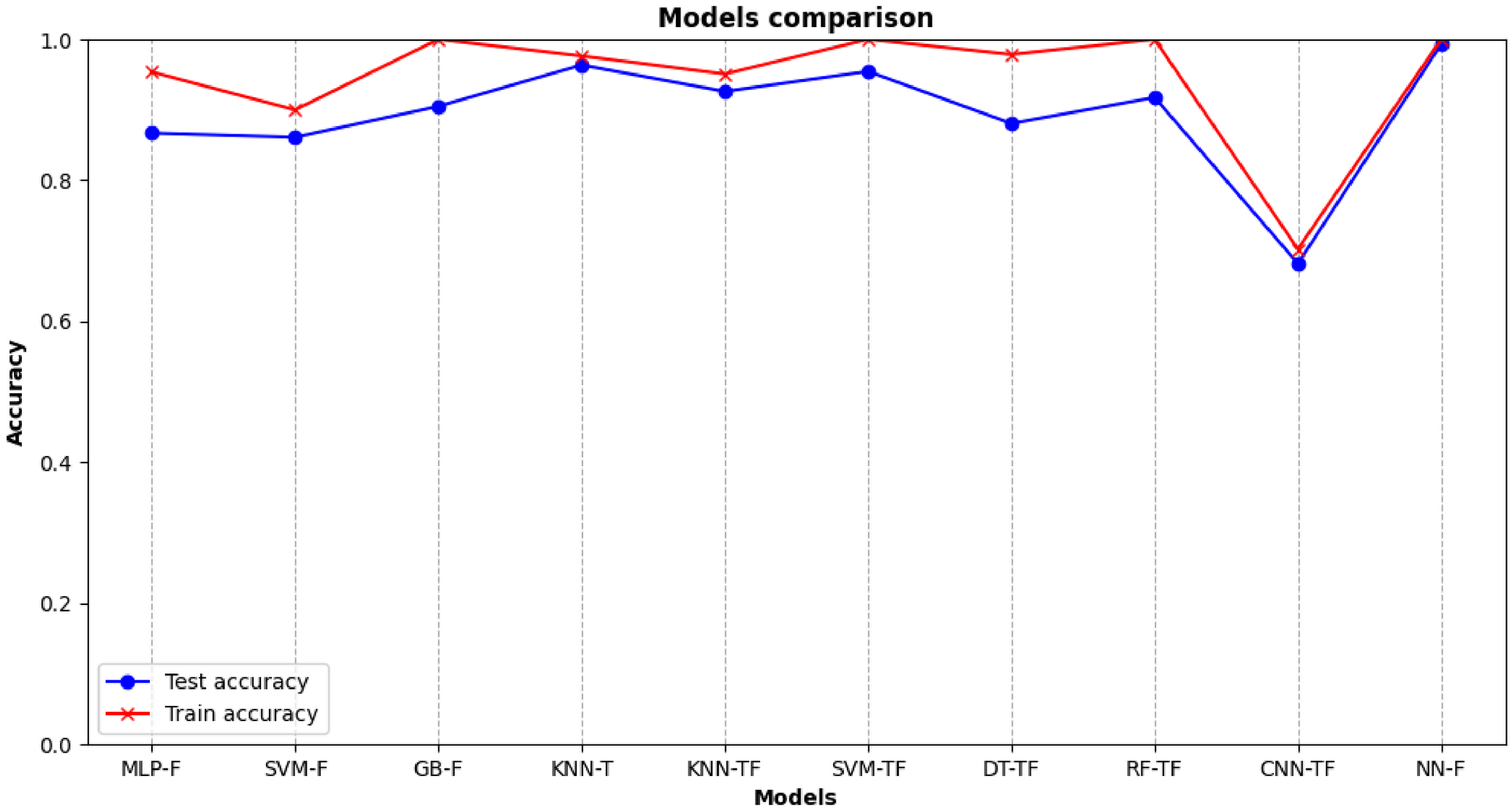
- **Data Augmentation:** The size of our data set is small.
- Fine-tuning parameters at play **(there are many)**
- Trying out different model’s structure.

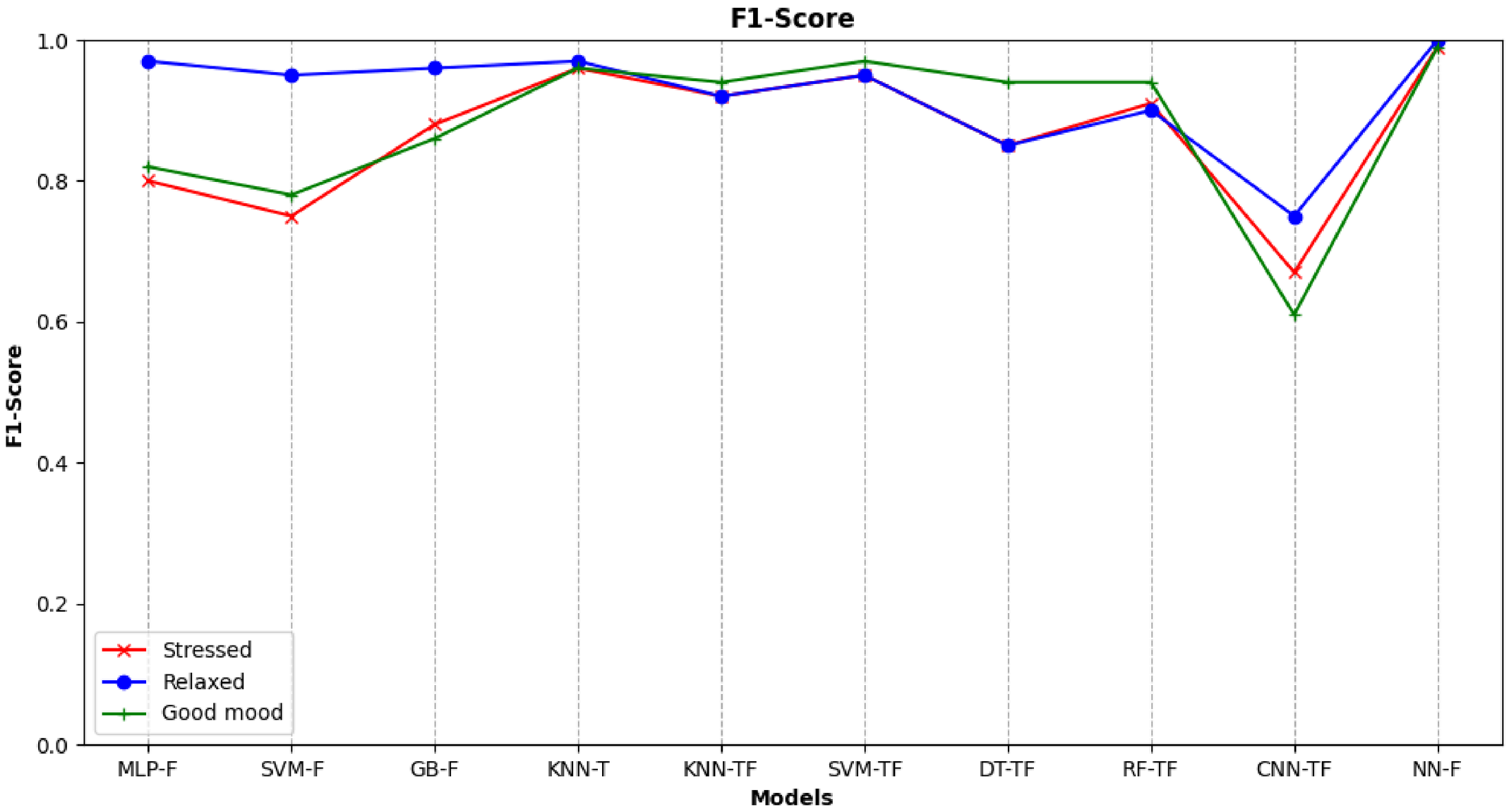
SUMMARY

ABBREVIATION

The models’ names displayed with their **test** and **train accuracy: [Name]-[Feature]**

- **TF:** Time-frequency domain
- **T**: Time domain
- **F**: Frequency domain


Models comparison
1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
Test accuracy
Train accuracy
MLP-F
SVM-F
GB-F
KNN-T
KNN-TF
SVM-TF
DT-TF
RF-TF
CNN-TF
NN-F
Models


F1-Score
1.0
0.8
0.6
0.4
0.2
0.0
F1-Score
Stressed
Relaxed
Good mood
MLP-F
SVM-F
GB-F
KNN-T
KNN-TF
SVM-TF
DT-TF
RF-TF
CNN-TF
NN-F
Models

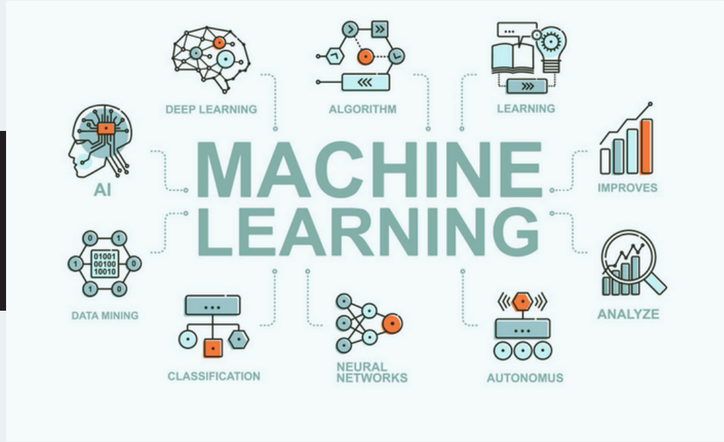
SUMMARY

- Out of the three types of feature extraction, the **frequency domain** seems to be the **most informative** with **99% and 100% test and train accuracy respectively** of the **Neural Network.**

- For this dataset, **time-frequency domain extraction** is **not so suitable** due to its computationally expensive nature and the **small dataset size**.

- This is evident in the application of **CWT and CNN** in classifying the EEG signals, this **model performed worst** with **only 68% and 70% test and train accuracy respectively**.

- Other models prove to be **highly effectiv**e in this classification task with **no less than 86%** test accuracy.

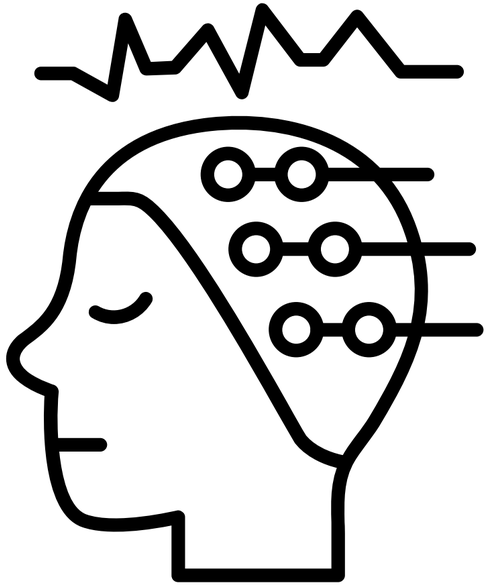


FUTURE RESEARCH DIRECTIONS

- **Dataset Expansion:** Collect data from a larger, diverse pool
- **Advanced Models:** Explore LSTM and Transformer models
- **Signal Processing:** Enhance techniques like ICA
- **Integration:** Combine EEG with other physiological signals
- **User-Friendly Devices:** Develop non-invasive, wearable EEG devices
- **Real-World Validation:** Conduct extensive field studies
- **Privacy & Ethics:** Ensure robust encryption and address ethical concerns

MENTAL STRESS DETECTION
USING EEG HEADSET

THANKS FOR LISTENING



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