HUMAN EMOTION DETECTION

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STEP-1: Prototype Selection

1. Problem Statement

Simple categories for human facial expressions include joyful, sad, surprised, scared, angry, disgusted, and neutral. Specific groups of facial muscles are triggered when we experience facial emotion. An expression's signals can provide a wealth of information about our mental state. We can easily and inexpensively assess the effects that content and services have on audiences and users by using face emotion recognition.

Medical industry might make use of these indicators. Having more knowledge about the emotional condition of patients while receiving treatment can help healthcare providers serve patients better. In order to continuously generate the desired content, entertainment producers can track audience participation at events. Accordingly, certain things would be shown to the patients. Basically, We need to build certain model that detects the human emotions from their facial expressions.

2. Market/Customer/Business Need Assessment

This generation is completely powered by Artificial Intelligence & Machine Learning, the topic of detecting human emotions via facial recognition is widely used in many industries. Artificial intelligence and machine learning-based emotion detection software understands human emotions from non-verbal visual data. Businesses can gain a deeper understanding of their clients by taking advantage of these nonverbal sentiments. As a result, businesses can enhance the client experience and raise revenue. It is not always possible that the customer will be speaking and telling the negative reviews. So, they might be hiding their real reviews inside. To get those unspoken reviews the best solution is emotion detection using facial recognition.

3. Target Specifications and Characterization

Assess personality traits in interviews - A personal interview is a fantastic technique to get to know prospective employees and determine whether they are a suitable match for the role. It is not always possible to assess a candidate's personality in such a brief amount of time. Emotion detection can assess and measure a candidate's emotions through facial expressions. It helps interviewers to understand a candidate's mood and personality traits. The human resource (HR) can benefit from this model.

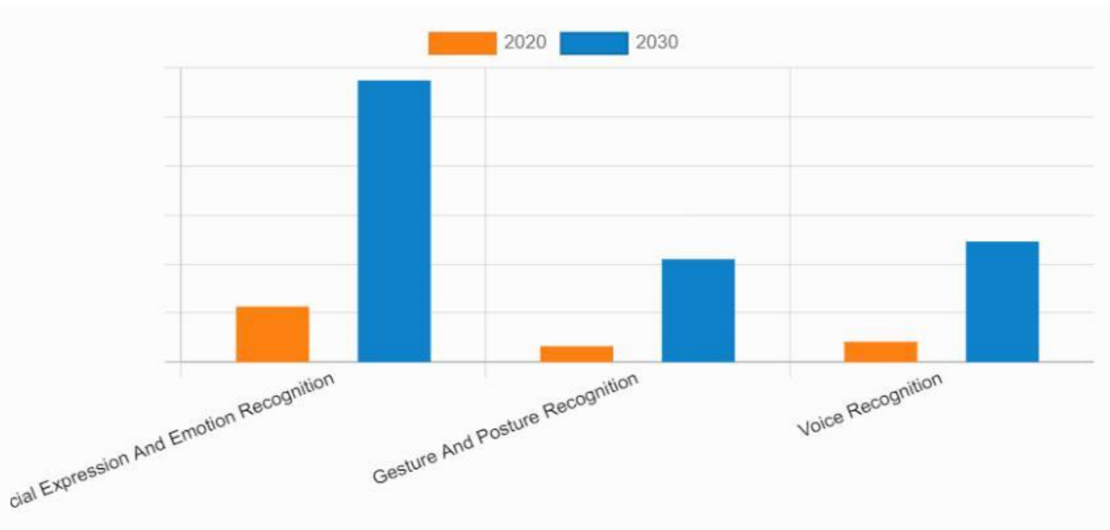
Product testing and client feedback - The product industry can better comprehend the true sentiments of customers by using emotion detecting technology. Companies can set up product testing sessions, record them, and then analyze the footage to find and evaluate the facial expressions that change throughout the session. Since AI is used to power emotion recognition, it offers the best way to assess consumer reaction to new product introductions.

Healthcare - Healthcare centers use AI facial recognition to analyze the moods of patients in the waiting areas. This enables specialists to schedule consultations earlier for patients who are experiencing worse symptoms.

Finance & Banking - Banking apps with built-in Emotion AI technology are the standard use case in the finance industry. It recognizes facial expressions using the sensors that are already built in. You can use eye tracking because modern smartphones can now accurately track a user's eye position thanks to front-facing cameras. You should take note of this and make changes if the clients' interest begins to fade, and they start rolling their eyes away.

4. Benchmarking Alternate Products

The global emotion detection market was valued at $18.8 billion in 2020, it is projected to reach $103.1 billion by 2030 growing at a rate of 18.7% from 2021 to 2030. The keys players in this market are Amazon, Oxygen Forensics, Affectiva, CrowdEmotion, IBM, Kairos, SkyBiometry etc. All these companies are efficiently using the concept of emotion detection using facial recognition. According to the bar graph below, We can analyze that Emotion Recognition & Facial Expression is leading the market at present and in future as well.



IBM – Early this year IBM Watson released textual emotion detection as a new functionality within the Alchemy Language Service and Tone Analyzer on the Watson developer cloud. Since then, it has been continuously improving its services.

Amazon – Amazon has its own service called 'Rekognition' . They have been providing services to the police department. Initially it used to give less accurate results for people with darker skin. Now it has been solved by AI & ML experts at Amazon Rekognition. It has been assessing emotions in faces along a sliding scale for seven categories: "happy," "sad," "angry," "surprised," "disgusted," "calm," and "confused."

Oxygen Forensics – It provides its software to the FBI and other agencies to extract data from smartphone. Now it has also added emotion detection to it. This feature has been helping the investigators to sort through thousands of images that could be turned as digital evidence. Officers can now search for a specific face in an evidence trove, or cluster images of the same person together. They can also filter faces by race or age group, and emotions such as "joy" and "anger."

5. Applicable Patents

Emotion recognition method and device - Emotion recognition is performed by extracting a set comprising at least one feature derived from a signal and processing the set of extracted features(s) to detect an emotion therefrom. The voice signal is low pass filtered prior to extracting therefrom at least one feature of the set. The cut-off frequency for the low pass filtering is typically centered around 250 Hz. The features are e.g., statistical quantities extracted from sampling a signal of the intensity or pitch of the voice signal.

Method of emotion recognition - A method is disclosed in the present invention for recognizing emotion by setting different weights to at least of two kinds of unknown information, such as image and audio information, based on their recognition reliability, respectively. The weights are determined by the distance between test data and hyperplane and the standard deviation of training data and normalized by the mean distance between training data and hyperplane, representing the classification reliability of different information.

The method is capable of recognizing the emotion according to the unidentified information having higher weights while the at least two kinds of unidentified information have different result classified by the hyperplane and correcting wrong classification result of the other unidentified information so as to raise the accuracy while emotion recognition.

6. Applicable Regulations

- Data protection and privacy regulations (Customers)
- Govt Regulations for small businesses
- Employment Laws
- Antitrust Regulations
- Regulations against false advertising

7. Applicable Constraints

- Face might be not well visible due to partial or total occlusion
- Face angle towards camera might be too high for a recognition algorithm to work properly
- Regular testing and maintenance of model necessary
- Labelled data is difficult to find and very expensive
- To train model we need real world datasets which is difficult to access
- Data processing is a hectic task

A) Feasibility

Before starting the project, feasibility study is carried out to measure theviable of the system. Feasibility study is necessary to determine if creating a new or improved system is friendly with the cost, benefits, operation, technology and time. Following feasibility study is given as below:

1. Technical Feasibility

Technical feasibility is one of the first studies that must be conducted after the project has been identified. Technical feasibility study includesthe hardware and software devices.

The required technologies (C++ language and CLion IDE) existed.

2. Operational Feasibility

Operational Feasibility is a measure of how well a proposed system solves the problem and takes advantage of the opportunities identifiedduring scope definition. The following points were considered for theproject's technical feasibility:

- The system will detect and capture the image of face.
- The captured image is then (identified which category)

3. Economic Feasibility

The purpose of economic feasibility is to determine the positive economic benefits that include quantification and identification. The system is economically feasible due to availability of all requirementssuch as collection of data from

- JAFFE
- COHN-KANADE

4. Schedule Feasibility

Schedule feasibility is a measure of how reasonable the project timetable is. The system is found schedule feasible because the system is designed in such a way that it will finish prescribed time.

B) Viability

Face expression recognition systems have improved a lot over the past decade. The focus has definitely shifted from posed expression recognition to spontaneous expression recognition. Promising results canbe obtained under face registration errors, fast processing time, and high correct recognition rate (CRR) and significant performance improvements can be obtained in our system. System is fully automatic and has the capability to work with images feed. It is able to recognize spontaneous expressions. Our system can be used in Digital Cameras wherein the image can be captured only when the person smiles. In security systems which can identify a person, in any form of expression he presents himself. Rooms in homes can set the lights, television to a person's taste when they enter the room. Doctors can use the system to understand the intensity of pain or illness of a deaf patient. Our system can be used to detect and track a user's state of mind, and in mini-marts, shopping center to view the feedback of the customers to enhance the business etc.

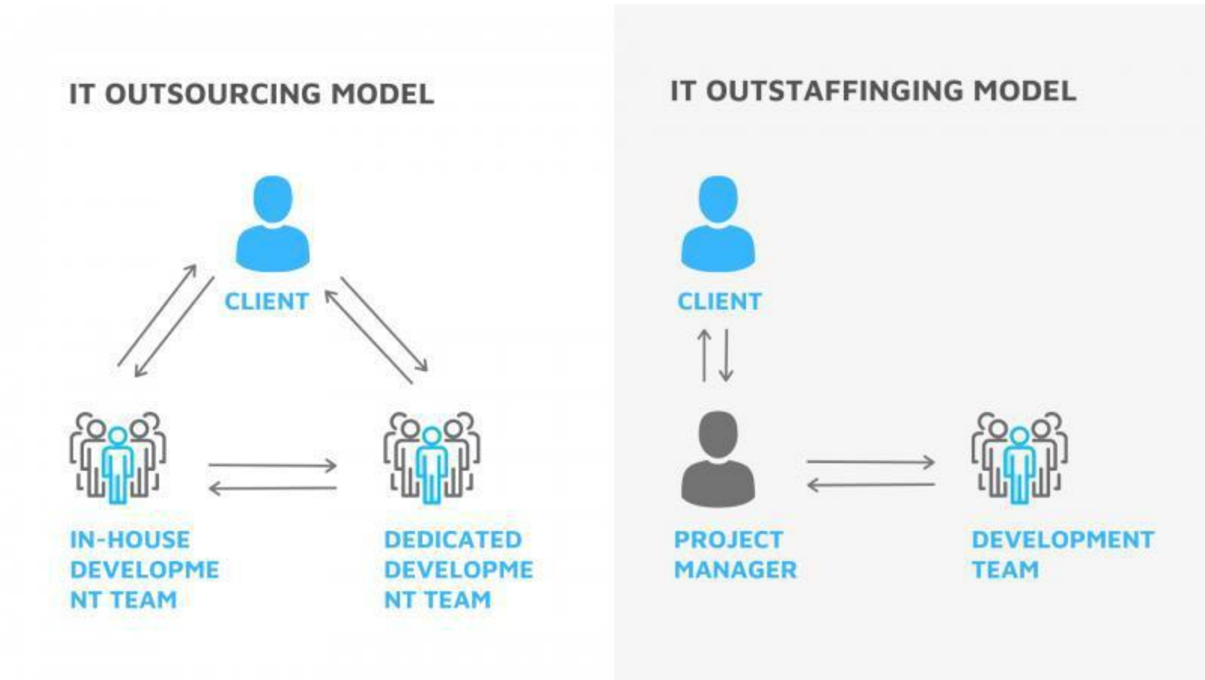
C) Monetization

This can be directly monetized by directly integrating the model to a music app. We can develop an which detects the persons mood by using the device camera to initiate its operations.

The model can also used by movie production houses. They can utilize infrared camera in the movie hall to collect analyze audience reception of the movie.

We can monetize using:

1) In-App Purchases
2) Advertising
3) Sponsorship
4) Model Outsourcing
5) Marketing



Step 2: Prototype Development

Implementation

```
cd /content/drive/My Drive/Face Emotion Detection
```

```
/content/drive/My Drive/Face Emotion Detection
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import cv2
```

```
dataset=pd.read_csv('Dataset/fer20131.csv')
dataset
```

	emotion	pixels	Usage
0	0	70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...	Training
1	0	151 150 147 155 148 133 111 140 170 174 182 15...	Training
2	2	231 212 156 164 174 138 161 173 182 200 106 38...	Training
3	4	24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...	Training
4	6	4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...	Training
...	...	...	...
35882	6	50 36 17 22 23 29 33 39 34 37 37 37 39 43 48 5...	PrivateTest
35883	3	178 174 172 173 181 188 191 194 196 199 200 20...	PrivateTest
35884	0	17 17 16 23 28 22 19 17 25 26 20 24 31 19 27 9...	PrivateTest

```
d=dataset['pixels'][0].split(' ')
```

```
o=np.array(d).astype('float32')
```

```
o=o.reshape((48,48))
```

```
o.shape
```

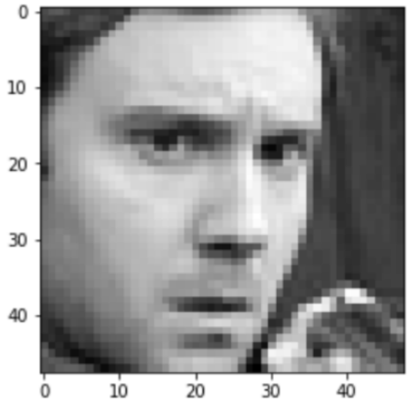
```
(48, 48)
```

```
o=o/255
```

```
o
```

```
array([[0.27450982, 0.3137255 , 0.32156864, ..., 0.20392157, 0.16862746,
        0.16078432],
       [0.25490198, 0.23921569, 0.22745098, ..., 0.21960784, 0.20392157,
        0.17254902],
       [0.19607843, 0.16862746, 0.21176471, ..., 0.19215687, 0.21960784,
        0.18431373],
       ...,
```

```
plt.imshow(o,cmap='gray')
```




```
emotion = {'Angry': 0, 'Disgust': 1, 'Fear': 2, 'Happy': 3,
           'Sad': 4, 'Surprise': 5, 'Neutral': 6}
emo     = ['Angry', 'Fear', 'Happy',
           'Sad', 'Surprise', 'Neutral']
```

```
len(dataset)
```

In [0]:

```
len(dataset)
```

Out[0]: 35887

In [0]:

```
images=[]
labels=[]
for i in range(0,len(dataset)):
  if dataset['emotion'][i]==0 or dataset['emotion'][i]==3 or dataset['emotion'][i]==4 or dataset['emotion'][i]==5 or dataset['emotion'][i]==2:
    d=dataset['pixels'][i].split(' ')
    o=np.array(d).astype('float32')
    o=o.reshape((48,48))
    o=cv2.cvtColor(o,cv2.COLOR_GRAY2RGB)
    images.append(o)
    labels.append(dataset['emotion'][i])
```

In [0]:

```
images=np.array(images)
labels=np.array(labels)
```

In [0]:

```
np.save("images",images)
np.save("labels",labels)
```

In [0]:

```
face_class=cv2.CascadeClassifier('haarcascades\haarcascade_frontalface_default.xml')
```

In [146…

```
img=images[3]
```

In [3]:
```
cd /content/drive/My Drive/Face Emotion Detection
```

```
/content/drive/My Drive/Face Emotion Detection
```

In [0]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import cv2
```

In [5]:
```
dataset=pd.read_csv('Dataset/fer20131.csv')
dataset
```

Out[5]:

	emotion	pixels	Usage
0	0	70 80 82 72 58 58 60 63 54 58 60 48 89 115 121...	Training
1	0	151 150 147 155 148 133 111 140 170 174 182 15...	Training
2	2	231 212 156 164 174 138 161 173 182 200 106 38...	Training
3	4	24 32 36 30 32 23 19 20 30 41 21 22 32 34 21 1...	Training
4	6	4 0 0 0 0 0 0 0 0 0 0 0 3 15 23 28 48 50 58 84...	Training
...	...	...	...
35882	6	50 36 17 22 23 29 33 39 34 37 37 37 39 43 48 5...	PrivateTest
35883	3	178 174 172 173 181 188 191 194 196 199 200 20...	PrivateTest
35884	0	17 17 16 23 28 22 19 17 25 26 20 24 31 19 27 9...	PrivateTest

```
emotion = {'Happy': 1,
           'Neutral': 0}
```

```
len(dataset)
```

35887

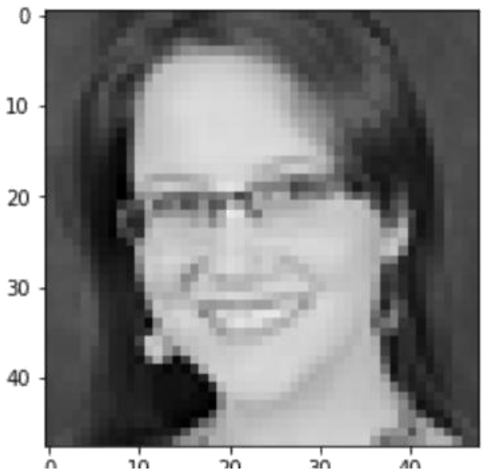
```
images=[]
labels=[]
for i in range(0,len(dataset)):
  if dataset['emotion'][i]==3:
    d=dataset['pixels'][i].split(' ')
    o=np.array(d).astype('float32')
    o=o.reshape((48,48))
    o=cv2.cvtColor(o,cv2.COLOR_GRAY2RGB)
    o=o/255
    images.append(o)
    labels.append(1)
  if dataset['emotion'][i]==6:
    d=dataset['pixels'][i].split(' ')
    o=np.array(d).astype('float32')
    o=o.reshape((48,48))
    o=cv2.cvtColor(o,cv2.COLOR_GRAY2RGB)
    o=o/255
    images.append(o)
```

```
o=o.reshape((48,48))
o=cv2.cvtColor(o,cv2.COLOR_GRAY2RGB)
o=o/255
images.append(o)
labels.append(0)
```

```
images=np.array(images)
labels=np.array(labels)
```

```
np.save("images_smile_nuetral",images)
np.save("labels_smile_nuetral",labels)
```

```
plt.imshow(images[1])
```



Step 3: Business Modelling

The Buisness Model for human emotion detection is a simple outsourcing based one. Developers can build and modify their model based on their clients requirement.

This can be done in the following ways:

Market Research – In the film industry, market research is generally qualitative and the data that is collated from surveys, reviews, and post-screening reactions is usually done manually. Some film companies, however, are taking advantage of emotion detection software and are using it to determine how moviegoers are enjoying their films. They do this by letting the software capture people’s faces and track facial behavior using infrared cameras during movie screenings.

All this is done in real-time which generates reliable data, helping movie production companies get a more accurate picture of audience responses. Ultimately, what these companies get out of this, is greater insight into what provokes an emotion.

Digital Advertising – Many of the most successful marketing campaigns and initiatives are focused on eliciting emotions. This is how companies or brands connect with their audiences. Digital marketing professionals are leveraging the power of emotion detection to understand the emotions of their potential customers to improve customer experiences and to create a lasting bond.

To begin with, analyzing various facial expressions and behavior can help to figure out the emotional state of a customer. This, subsequently, helps to recommend products that will satisfy the customers' requirements and expectations. When your content or

brand can connect with prospective buyers emotionally, it will drive them to make a purchase. Hence, it will boost your business.

Furthermore, being able to adjust marketing dynamically, based on the real-time responses of your audience, will empower marketers to provide the right message at the right time to the right person.

One-on-one Interviews – Companies are not only using emotion-detection technology for consumer-facing applications. Some employ this technology to screen prospective candidates based on factors like body language and mood. In doing so, a company is able to find the person whose personality and characteristics are best suited to the job. By analyzing body language and facial expressions, the algorithm can predict how the candidate might react or behave in certain situations. It also can pick up whether or not a candidate is being truthful, as well as their general confidence levels based on how emotions change during responses. Ultimately disposing of prolonged hiring processes.

Step 4: Financial Modelling (equation) with Machine Learning & Data Analysis

Abstract: Along with the fourth industrial revolution, research in the biomedical engineering field is being actively conducted. Among these research fields, the brain–computer interface (BCI) research, which studies the direct interaction between the brain and external devices, is in the spotlight. However, in the case of electroencephalograph (EEG) data measured through BCI, there are a huge number of features, which can lead to many difficulties in analysis because of complex relationships between features. For this reason, research on BCIs using EEG data is often insufficient. Therefore, in this study, we develop the methodology for selecting features for a specific type of BCI that predicts whether a person correctly detects facial expression changes or not by classifying EEG-based features. We also investigate whether specific EEG features affect expression change detection. Various feature selection methods were used to check the influence of each feature on expression change detection, and the best combination was selected using several machine learning classification techniques. As the best result of the classification accuracy, 71% of accuracy was obtained

with XG-Boost using 52 features. EEG topography was confirmed using the selected major features, showing that the detection of changes in facial expression largely engages brain activity in the frontal regions.
Keywords: machine learning; classification; feature selection; BCI; EEG

1. **Introduction**

Along with the fourth industrial revolution, data-driven research in the biomedical engineering field has been actively progressing. The brain–computer interface (BCI) is one of the emerging topics in the field that studies the direct interaction between the brain and external devices. With the development of devices capable of measuring neural activity, BCI research is actively progressing. Through the BCI, one can understand the information represented in the brain signals and predict action only from the brain signals. In particular, it is possible to measure the emotional state of the subject by capturing relevant brain signals with the BCI. Emotion recognition has been used in various application fields as a method of grasping human emotion states through computer systems. Emotions can be objectively classified through physiological signals such as blood pressure response, skin response, pupil reflex, and brain signals. Among them, recognizing emotions using brain signals has recently attracted great attention. Such systems often harness the electrical activity of the brain measured by tens of electrodes placed on the scalp, which is termed electroencephalography (EEG). Therefore, it is important to find major features in EEG data because the dimensionality of potential EEG features can be huge and the relationship between features is complex. In many studies, to analyze EEG data for the BCI, the feature selection technique has been widely used. The feature selection technique can reduce the complexity of the model and help improve accuracy. In addition, efforts to infer human emotional states by applying machine learning techniques are in progress. For instance, recent studies have applied a machine learning technique to classify mental states (concentration and drowsiness) from EEG data with very high accuracy. Today, machine learning algorithms are being used in various applications that deal with data. Machine learning can be classified into supervised learning and unsupervised learning according to the type of data used for learning.

If the training data used for learning contain a label that means the correct answer, it is called supervised learning, and it is called unsupervised learning when learning without a label. In addition, machine learning is used as a model for classification when the presented label means an individual category, and is used as a regression model when the label is a continuous variable. This study focuses on classification with supervised learning, where the label consists of the binary information of the success of detection of facial expression changes—e.g., ‘1’ if a person correctly detects a facial expression change and ‘0’ if the person incorrectly does it. Therefore, the EEG-based BCI was built in this study to predict whether or not a person correctly detects the facial expression changes of others. Such a BCI would be able to help us to develop an intelligent system to evaluate social interactions of individuals and assist to improve one’s empathic skills. We utilized machine learning methodology with a feature selection technique for classifying EEG data.

The purpose of this study is to derive the results of how the extracted main features affect the prediction of the correct detection of facial expression changes. Feature selection methods such as Fisher score, chi-square, mutual information, and Gini importance were used to examine the influence of each feature and to select the main features. In addition, random forest, decision tree, XG-Boost, and support vector machine (SVM) were used to classify EEG into correct and incorrect facial expression change detection. The combination of the methodologies that showed the best classification accuracy was selected using the proposed feature selection technique and machine learning classification technique. Using the set of key features representing the highest classification accuracy, we examined specific brain areas important when people detect the facial expressions of others. The following sections of the paper describe the details of the research conducted. Section 2 presents the extensive algorithms and methodologies used in this study. Section 3 describes the data and experimental methods used. Section 4 describes the experimental results. Section 5 discusses the significance and limitations of this study, and Section 6 describes the conclusion.

2. Methods

In this section, we describe the feature selection methods and classification methods. Some feature selection methods and classification techniques are explained through detailed formulas to understand them. This session will help you understand how each technique will be used. With this, we used several feature selection methods and classification methods to find the best combination for BCI data analysis.

2.1. *Feature Selection Methods*

In building a classification model, it is a very important process to select features that affect the classification result. In this study, popular feature selection methods were used, such as F-score, chi-square, and mutual information, which are univariate feature selection methods. In addition, a feature selection technique using Gini importance was also used. These variable selection methods rank variables in consideration of the influence between the target variable and the dependent variable. By using these feature selection methods, the complexity of building the model can be greatly reduced.

2.1.1. *Fisher Score*

The Fisher score (F-score) is one of the most popular feature selection methods. F-score is a univariate selection method that selects the optimal features based on a statistical model. It can be used mainly in linear models. The characteristics between heterogeneous classes are different, and the F-score increases as the characteristics between homogeneous classes are similar. After statistically analyzing the relationship between the dependent variable and independent variable, the influence of each independent variable is derived with weight. F-score has the advantage of fast calculation, and it is easy to check the influence of each variable. The equation for calculating the F-score is as follows.

$$Fscore_i = \frac{|S_B|}{|S_W|} \quad (1)$$

$$S_B = \sum_{i=1}^{C} n_i (u - u_i)(u - u_i)^T \quad (2)$$

$$S_W = \sum_{i=1}^{C} \sum_{x \in c_i} (x - u_i)(x - u_i)^T \quad (3)$$

where the F-score is the ratio of between-class scatter (S_B) and within-class scatter (S_W), C is the total number of classes, and n_i is the number of samples belonging to c_i.

2.1.2. *Chi-Square*

Chi-square is also a popular feature selection method. This technique statistically checks the relationship between each independent variable and class. Since the chi-square test measures the dependence of each variable, it is easy to identify independent variables that are not related to class. In other words, if there is no association between the dependent variable and the independent variable as a result of the statistical test, it is judged that the independent variable is not significant. The formula for chi-square is as follows:

$$Chi = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \quad (4)$$

where O_i is the observed value of each class, E_i is the expected value of each class, and k is the number of classes.

2.1.3. *Mutual Information*

Mutual information (MI) is one of the univariate selection methods. MI has the characteristic of using a nonparametric methodology. When the independent variable and the dependent variable are completely independent, the amount of information becomes 0, and when they are related, the number of information increases. If there is an inverse relationship, the number of information decreases. In other words, it is an indicator to judge how close the relationship between the variables is. The equation for calculating MI is as follows

$$MI(A, B) = \frac{P(A \cap B)}{P(A) * P(B)} \quad (5)$$

In the feature selection technique, MI is used to identify the dependency between the dependent variable and the independent variable. The higher the value, the higher the dependence and the influence.

2.1.4. *Gini Importance*

Gini importance is utilized to measure the importance of the feature. It is calculated based on Gini impurity. As the importance of a specific feature increases, the impurity of the corresponding node decreases significantly. Therefore, the lower the impurity, the higher the importance of the feature. Gini impurity becomes 0 when the values classified through nodes are heterogeneous, and 1 in the opposite case. The following is the formula for Gini impurity:

$$Gini(A) = 1 - \sum_{k=1}^{m} p_k^2 \quad (6)$$

where p_k is the ratio of data belonging to k class, and m is the number of classes. Impurity after classification can be measured through the above formula. The closer the impurity is to 0, the higher the homogeneity. The importance of each node can be measured through the measured impurity. The formula for the importance of a node is as follows:

$$I(C_j) = w_j Gini(C_j) - w_{j_{left}} Gini\left(C_{j_{left}}\right) - w_{j_{right}} Gini\left(C_{j_{right}}\right) \quad (7)$$

where w_j means the ratio of the number of samples corresponding to node C_j among the total number of samples. That is, the weight impurity of the parent node is subtracted from the sum of the weight impurity of the child nodes. Node importance can be used to measure how much each feature has an impact on creating a tree and classifying samples.

2.2. Classifiers

Classification is a matter of predicting a given category of data. Classification is being used in many areas today and is steadily used in the research field relevant to BCI. Classification can be classified into binary classification and multiple classifications according to the number of classes. In this study, the binary classification problem was the focus because the dataset was composed of two classes that indicate whether facial expressions were detected. The classifiers such as random forest, gradient boost, XG-Boost, and SVM were used to classify whether or not facial expressions are detected.

2.2.1.1.Random Forest

Random forest is an ensemble machine learning model. It is used for both classification and regression, like decision trees. The decision tree is one of the supervised learning methods to classify data through classification rules. The derived model is composed of a tree structure, which is easy to understand. However, it has a limitation of frequent overfitting of the training data. Therefore, a random forest was used to solve the overfitting problem. Since it generalizes and uses the result values of several randomly generated decision trees, the overfitting problem is significantly reduced. It uses a technique of bootstrap and aggregation (bagging) to generate a tree over a subset of the training data. It is advantageous for generalization because it aggregates the results of many trees through the voting technique.

2.2.2. Gradient Boost

Gradient boosting is a prediction model that can perform regression analysis or classification analysis and is an algorithm belonging to the boosting family of ensemble methods. It is an algorithm that creates several weak learners to make strong learners. The correct answer is predicted using the preceding tree, and the remaining residuals are predicted using the next tree. By repeating this process, the model builds a number of trees (weak learners). These trees are combined to create a strong classifier. To improve the performance of each classifier, errors must be quantified using a loss function, and residuals should be reduced. Gradient boosting uses the algorithm of gradient descent in the process and induces learning in a direction in which the loss function can be minimized.

2.2.3. *XG-Boost*

Since gradient boosting requires compute-intensive tasks, it is necessary to calculate it efficiently. XG-Boost is a machine-learning model created to compensate for the demerit of gradient boosting. It is similar to gradient boosting, but it controls the complexity of the tree by adjusting the loss function. Therefore, it has a faster operation speed compared to Mathematics 2021, 9, 2062 5 of 15 with the existing gradient boost. In addition, it supplements the problem of overfitting by using the random subsampling technique of each individual tree.

2.2.4. *SVM*

SVM is one of the most popular machine learning models. In this study, it was used as a binary classifier that classifies into two classes. It is a model that defines criteria for classification. These criteria are called the decision boundary, and the greater the number of features, the more complex it appears. The more accurate the decision boundary used to classify the data class, the higher the accuracy. However, it is difficult to accurately classify all data, so some outliers are ignored. The distance between the decision boundary and the support vector is called the margin. By adjusting the margin, the overfitting problem can be reduced. It can obtain various types of decision boundaries by using several kernel options. That is, the result of the model changes a lot according to the adjustment of the parameter value.

3. Data Analysis

3.1. Data Collection

3.1.1. Participants

Seventy-five participants (49 males, 26 females), aged 19–30 years (mean 22.96 ± 2.4 years old), volunteered to take part in the experiment. All reported having normal or corrected-to-normal vision with reportedly no neurological disorder or psychiatric illness. Of those, 10 participants were excluded due to a problem in data acquisition, and 14 due to an insufficient number of samples in any of the two classes. This exclusion left 51 participants' data for subsequent analyses.

3.1.2. Task

The main purpose of the task was to measure the perceptual sensitivity of individuals to emotional changes in others' facial expressions. The experiment was designed according to the previous study by Ha and Shim [32]. In every trial of the task, a fixation (white cross) was presented for 500 m/s at the centre of the screen. Then, an animated human face whose expression dynamically changed from neutral expression to emotional expression began to appear. Participants watched the animated face and reacted as quickly as possible by pressing the space bar on the keyboard when they recognized an emotion in the presented face (Figure 1a). The facial animation consisted of 26 facial expression images (created in Face-Gen Modeller, Singular Inversions, accessed on 27 July 2021), from neutral to emotional ones, where each image was displayed for 300 ms—a full presentation of the animated face thus took 7800 m/s. When participants pressed the button, the facial animation stopped, and the next response window was shown on the screen to ask which emotion participants recognized with numerical mapping of keys from 1 to 6: '1'= fear, '2' = sad, '3' = surprise, '4' = happy, '5' = angry, and '6' = disgust. Both male and female faces were presented, respectively. A trial for one of the six emotions for each gender was repeated 5 times, yielding a total of 60 trials in the task (6 emotions × 2 genders (male, female) × 5 repetitions) (Figure 1b).

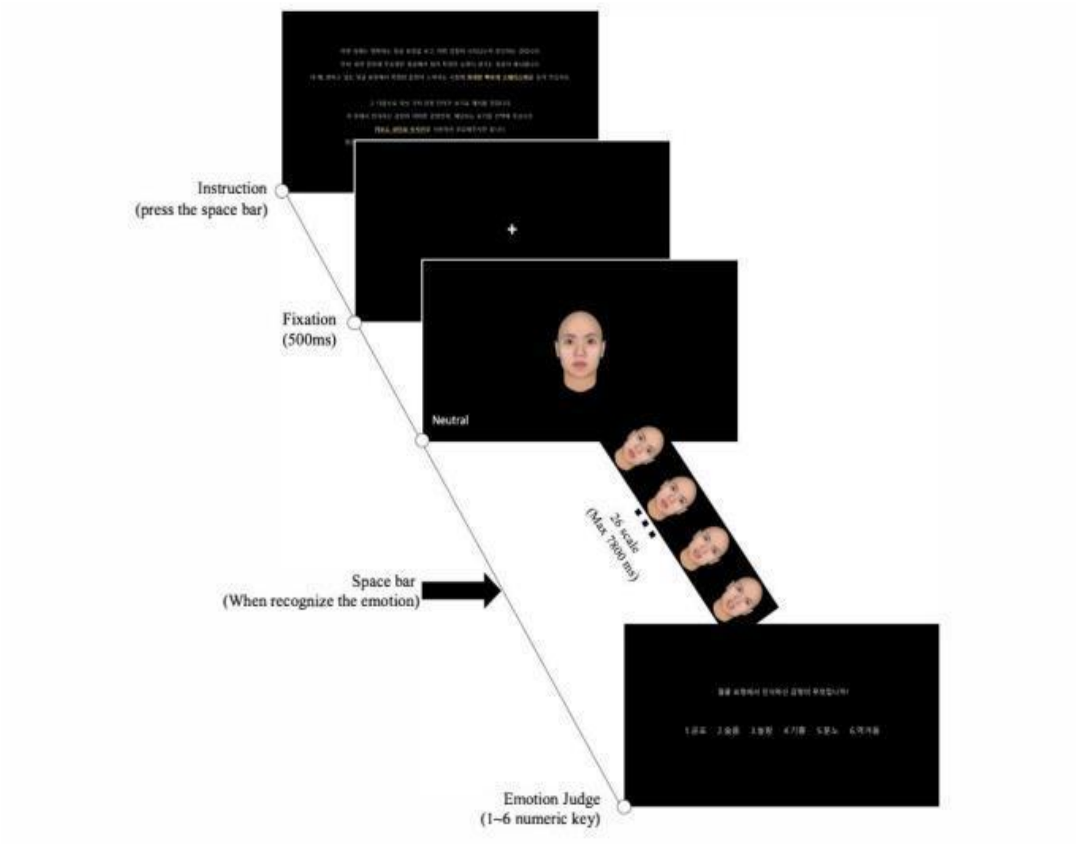
3.1.3. EEG Acquisition and Processing

EEG signals were acquired using 31-channel wet Ag/Cl electrodes (anti-champ, Brain Products GmbH, Gilching, Germany) at a sampling rate of 500 Hz. The acquired EEG signals were band-pass-filtered with 1 Hz and 100 Hz cut-off frequencies using a finite impulse response (FIR) filter. The position of 31 electrodes was determined following the 10/20 international system: FP1, FPz, FP2, F7, F3, Fz, F4, F8, FT9, FC5, FC1, FC2, FC6, FT10, T7, C3, Cz, C4, T8, CP5, CP1, CP2, CP6, P7, P3, Pz, P4, P8, O1, Oz, and O2 (Figure 1c). Additional electrodes were attached to the left mastoid as a ground and the right mastoid as a reference. The impedance of all electrodes was kept below 10 k Ohm.

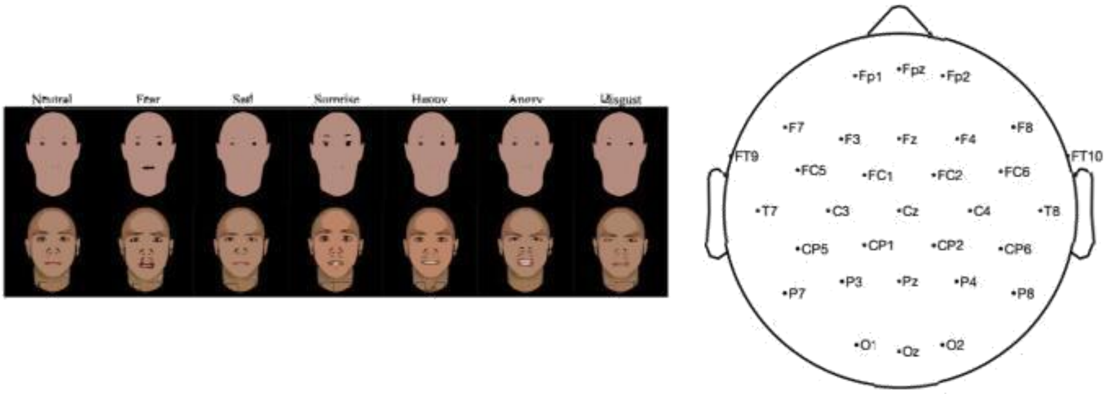
EEG pre-processing was conducted using the EEGLAB toolbox in MATLAB software (Math-words, Inc., Natick, MA, USA). First, the EEG signals were band-pass-filtered again with a 58–62 Hz notch filter to remove line noise using an FIR filter. Second, we eliminated noisy electrodes by investigating the correlation of a single channel with others. All rejected channels were spherically interpolated to simplify subsequent analyses. After interpolation, the common average reference (CAR) method was applied for re-referencing. Independent component analysis (ICA) was then used to remove ocular and muscle artefacts. The artefact component was detected using the IC-Label plugin that classified EEG-independent components (ICs) automatically. By using this tool, those ICs with any of the following labels that showed a label probability ≥0.8 were rejected: 'muscle' and 'eye'. An epoch of the EEG signal was extracted from 1200 m/s to 200 m/s before response onset (i.e., time to press the space bar) from each trial. The baseline period was set to be 0 m/s to 500 m/s after fixation onset.

The epoch was standardized by the baseline signal's mean and standard deviation. Short-time Fourier transform (STFT) was applied to each epoch with a window length of 256 m/s, and an overlap of 240 m/s. The log-transformed power spectrum obtained by STFT in each window was subdivided into 6 frequency bands: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), low-beta (13–20 Hz), high-beta (20–30 Hz), and gamma (30–50 Hz). The log-transformed power values within each band were averaged in each window, yielding a time–frequency data matrix with varying time size but fixed frequency size for each trial. After that, the information on the time window was averaged, leaving channel (31) and frequency (6) information for each trial.

The EEG dataset used in this study was aggregated from all EEG data of individual participants, where there were 50 trials of data on average for each participant. The aggregation yielded the EEG data of 2629 trials in total from 51 subjects. As described in the previous section, the analysis of EEG resulted in 186 features, including EEG spectral power values in 6 frequency bands at 31 EEG channels (i.e., electrodes) calculated in each trial. The size of the feature matrix was then 2629 × 186 (number of trials (samples) × number of features). Each trial (sample) in this data matrix was assigned the label of 1 if participants recognized facial expressions correctly or 0 if they did incorrectly



(a)



(b) (c)

Figure 1. Figure about an experiment to acquire data. (**a**) Experiment protocol; (**b**) facial expression stimuli; the upper row is female, bottom is male. From left to right, the first is neutral face and in turn, the extreme expression of each emotion is shown; (**c**) EEG montage.

3.2. Feature Selection

By using the feature selection methods, the influence of each independent variable on the dependent variable was calculated, and sorting was performed in the order of the largest influence. In order to derive the model result according to the change in the number of accumulated variables, the accuracy of the model was measured by adding major variables one by one in order. Through the procedure, the accuracy that changes as individual variables are added can be measured, and the number of accumulated variables with the highest classification accuracy can be identified. In this study, the combination with the highest classification accuracy was selected as the main feature. In addition to the method of adding a single variable in consideration of the interaction between the main variables, the method of selecting and combining the top 10 variables with high influence was additionally used. A combination was created and used from 10 variables selected through each feature selection method, and the combination variable with the highest classification accuracy was identified. However, when comparing the first feature selection method with the second feature selection method, the accuracy of the second method was low, so in this study, the combination created by gradually adding a major single variable was finally utilized.

3.3. Experiment Diagram

Figure 2 shows the diagram for the experiment. The first stage, the data acquisition stage, performs data collection and pre-processing through experiments. In the next step, the feature selection methodology is applied. The priority of features is checked through the feature selection methodology. Then, classification modelling is performed using machine learning methodologies. The extracted features are used for classification modelling. The performance of a machine learning model is checked through its accuracy. Then, the model with the highest classification accuracy is analyzed. In the final stage, we analyze how key features are located in scalp topography and which sub-bands are mainly used.

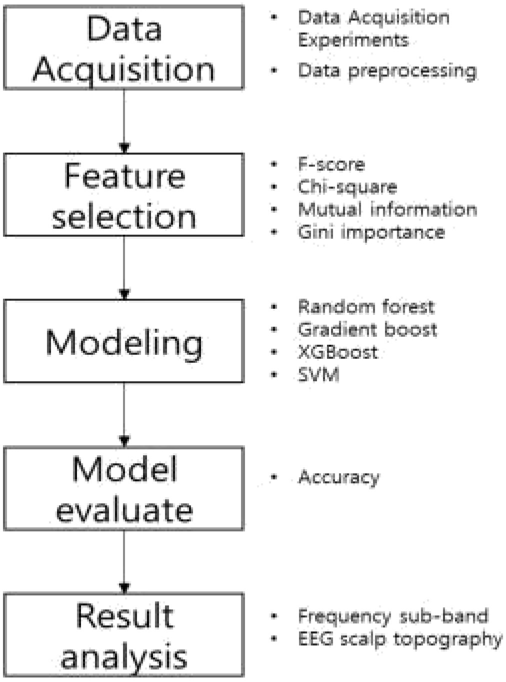


Figure 2. Diagram representing the experimental process. It represents the various methodologies and work content utilized at each stage.

3.5. Base Score

Base score is the classification accuracy of basic machine learning methods. By comparing the feature selection-based accuracy and the base score, we checked whether the feature selection methods affect the accuracy improvement. It was calculated using the aforementioned machine learning methods. After fixing the random seed, classes were classified through each method. In this study, accuracy was utilized to evaluate the performance of the model. The expression for accuracy is as in Equation (8).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (8)$$

True positive (TP) and true negative (TN) mean that the predicted result of the model and the actual value are the same or different. False positive (FP) and false negative (FN) mean the opposite of TP and TN. Accuracy is the number of correctly predicted data divided by the total number of data. The classification results are shown in Table 2.

Table 2. The accuracy of the ensemble model that used several models together was the highest.

Data	Random Forest	Gradient Boost	XGBoost	SVM	Ensemble
BCI_186	0.681	0.682	0.680	0.680	0.690

As a result of calculating the base score, the average accuracy of each model was about 68%. In this study, the standard score was set to 69%, and the improvement of the performance with the feature selection was tested.

4. Results

This section describes the results of the study. It describes the results of variable selection through feature selection, classification results for each model, and the results of BCI data analysis through major variables. The results of data classification are presented in detail in the form of a table, and EEG topography is also presented. This section describes the key variables selected and their regions of expression in the brain.

4.1. Result of Feature Selection

4.1.1. Result of Adding Influential Feature

Feature influence was measured through several feature selection methods. After sorting the features in the order of the measured influence, one variable from highest to lowest influence was cumulatively added one by one for each trial to derive the classification result. Both the training data and the test data were fixed using the same random seed value. The classification results from applying the feature selection methods are shown below in Table 3.

Table 3. The result of calculating the number of features showing the highest classification performance when classified while adding features one by one.

Feature Selection & Classification Model		F-Score	Chi-Square	Mutual Information	Gini Importance	Ensemble
Random Forest	Accuracy	69.4%	69.2%	69.2%	69.0%	70.0%
	The number of features	38	30	80	111	157
Gradient Boost	Accuracy	69.6%	69.0%	70.0%	69.2%	69.2%
	The number of features	34	41	8	7	129
XGBoost	Accuracy	70%	**71.0%**	69%	70.0%	70.0%
	The number of features	76	**52**	6	8	73
SVM	Accuracy	68.3%	68.3%	68.3%	68.3%	68.3%
	The number of features	1	1	1	1	1

Table 3 shows the results of machine learning techniques applied to the feature selection method. Most of the algorithms, except SVM, have improved classification accuracy through feature selection methods. In particular, the XG-Boost model based on the top 52 features extracted through chi-square showed the highest performance with 71% classification accuracy. This is a result of using only about 36% of the total features, and it can be seen that it not only improved accuracy but also improved the computational efficiency of the model.

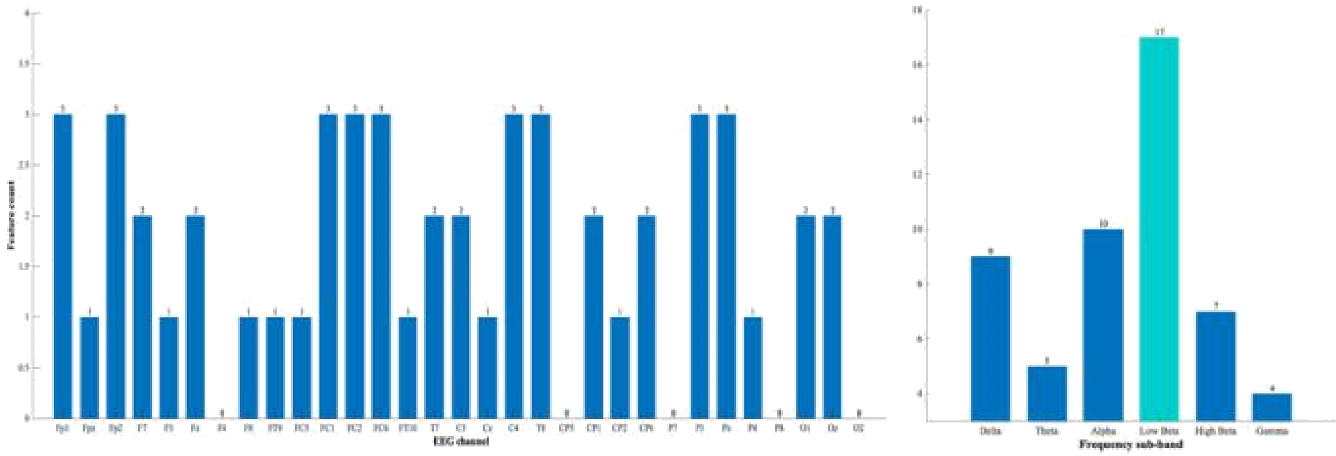
4.1.2. Result of Feature Subset

All possible combinations were created using the top 10 features selected through feature selection methods. The accuracy of the classification model was calculated using a combined subset of features. As seen in the previous experiment, the dataset was fixed through random seeds. The classification results are shown in Table 4.

Table 4 shows the results of machine learning methods using main feature subsets. Table 4 shows lower accuracy compared with Table 3. Most of the classification accuracy shown in Table 4 is similar to that of the base score. However, the accuracy of the combination of features using Gini importance tends to be somewhat high. In particular, when using gradient boost, it shows an accuracy of 70.3% through four features. It has a somewhat lower classification accuracy than that of the previous experiment but can bring a great effect in terms of computational efficiency. From Tables 3 and 4, it can be seen that applying the feature selection method can have a great advantage in terms of accuracy and computational efficiency. In particular, when using chi-square and XG-Boost, there was a 2% improvement in accuracy compared to the base score. When Gini importance and gradient boost were used, a classification accuracy of 70.3% was obtained with four features.

4.2. Result of BCI Interaction

In the model with the highest performance (71%, chi-square and XG-Boost), we counted the number of selected features for each EEG channel and frequency sub-bands to examine the spatial distribution of the selected features over the whole brain. We observed that the selected features were widely distributed over almost all EEG channels (26 out of 31 channels, Figure 3a), indicating that there were no specific EEG channels and brain areas that dominantly generated key features for classification. We additionally divided the entire channels into eight brain areas to compare the number of selected features among different brain areas: prefrontal (Fp), frontal (F), front central (FC), temporal (T), central (C), centro-parietal (CP), parietal (P), and occipital (O) areas. Then, we calculated the average number of selected features per channel in each area as the number of channels varied across the areas. As a result, the fronto-central (FC) area exhibited the largest average number of selected channels, followed by the prefrontal (Fp) area showing the second largest (Fp: 2.3, F: 1.2, FC: 2.5, T: 1.75, C: 2, CP: 1.25, P: 1.4, O: 1.3). Accordingly, we found that while most brain areas provided EEG features useful for classification, the fronto-central and prefrontal areas contributed the most.



(a) (b)

Figure 3. Feature count distribution. The features selected from the model with the highest accuracy (71%, chi-square and XGBoost) are counted for each dimension. (**a**) EEG channel. It is difficult to find the dominant spatial pattern; (**b**) Frequency sub-band. The low-beta, the frequency band with the highest feature count, is shown in light blue.

Next, we analyzed the spectral distribution of the number of selected features over frequency sub-bands given as follows: delta, theta, alpha, low-beta, high-beta, and gamma. The largest number of selected features was found in the low-beta band (Figure 3b). Low beta (12–20 Hz) activity is known to be associated with increased mental states of high engagement, performance, and concentration, as well as with emotional stimulus processing and social interactions. Therefore, the result here indicates that the modulation of low-beta activity may underlie the correct recognition of the facial expressions of others. Figure 4 depicts the EEG scalp topography of the chi-square selection importance rank score in the low-beta band. We calculated the importance rank score as shown in Equation (9) in the chi-square variable selection:

$$Importance\ rank = 1 - \left(\frac{ascending\ order}{feature\ size}\right) \tag{9}$$

where an ascending selection order indicates the order in which a given feature was selected (from 1 to the number of features) and a feature size denotes the total number of features. Note that the importance rank score ranges from 0 to 1. For instance, if the chi-square variable selection results in the feature index in the following order: 153, 95, 10, etc. and the total number of selected features is 186, the importance rank score of feature 153 is 0.9946 and that of the lastly selected feature is 0. The topography demonstrates that low-beta activity at the frontal and parietal areas tended to yield more important features for classification. This result could be related to the role of working memory (WM) in the recognition of facial expressions. It is known that loading into WM reduces the plasticity of facial expression recognition, leading to the false perception of facial stimuli. As the prefrontal and parietal areas are primarily engaged in WM , our observation of the distribution of important features over frontoparietal areas may reflect the operation of WM in facial expression recognition. In addition, the low-beta activity of parietal areas provides a substrate of WM that can synergistically integrate sensory information and executive commands from frontal areas . Accordingly, our result of important low-beta features over fronto-parietal areas may indicate how well the visual information of facial expression is integrated with the function of emotional change detection in WM.