Chapter 11

OpenCV and DeepFace Approach on Image Processing: Applications on Street Interviews

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Abstract

Using Python-based face recognition technology, this work aims to forecast characteristics including age, gender, and moods of individuals shown in video uploaded on the YouTube platform from 2017 to 2021. This study particularly makes use of this method on individuals engaged in YouTube street interviews, focusing on issues related to the unemployment and economy.

The concordance and distribution of emotional variables alongside demographic variables such as age and gender were investigated using the "correspondence" analysis method, a multivariate technique that visualizes relationships among variables and categorical cross-relationships through graphical mapping.

Data concerning the emotional variance from every year between 2017 and 2021 were gathered. Data were especially separated, and unhappiness rates were computed as percentages from the gathered data. The study looked at the relationship between the unemployment rate for the particular years and the computed degree of discontent. Non-parametric statistical methods were seen more suitable in this phase of the research as the low data volume made normalcy testing impossible.

The value of facial recognition systems in demographic prediction and emotional evaluation is underlined by this work. Furthermore, it emphasizes the possible value of matching emotional forecasts with unemployment data in order to assess how economic changes affect personal emotional responses.

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This study emphasizes how improvements in artificial intelligence and data analysis could improve the understanding and answers for society issues. Therefore, it could motivate similar future study with great benefits in marketing, economics, and social sciences as well as highlight developments in data analysis and artificial intelligence.

1. Introduction

The study, which aims to determine demographic characteristics such as age, gender, and mood by analyzing the facial expressions of individuals featured in YouTube street interviews from 2017 to 2021, seeks to reveal the relationships between emotional analysis based on facial expressions and social variables such as the unemployment rate during the same period. In the literature review, studies on the use of facial recognition technology in demographic and emotional predictions are examined, and in the originality section, the uniqueness of the study is emphasized within the framework of these findings.

1.1. Literature Review:

Facial recognition technology for demographic predictions has garnered interest in artificial intelligence and image processing fields. A notable study by Levi and Hassner (2015) developed a model using convolutional neural networks (CNN) for age and gender prediction, achieving high accuracy rates on a large-scale facial dataset. This work highlights CNN's effectiveness in demographic analysis and classification accuracy for age and gender (Levi & Hassner, 2015).

In emotion analysis, transfer learning and deep learning are frequently used to attain high accuracy on smaller datasets. Sabri and El-Bakry (2021) applied models pre-trained on large datasets to perform facial expression analysis on limited data, demonstrating that transfer learning enables effective emotion predictions even with small datasets. This study emphasizes transfer learning's importance in emotion analysis when large datasets are unavailable (Sabri & El-Bakry, 2021).

1.2. Significance & Originality of the Study

Facial recognition systems play an important role in measuring responses to societal emotional rates and examining correlations with various other variables. The DeepFace detection and recognition model used here can be further enhanced by integrating additional parameters, thereby improving the model's accuracy beyond the current 76% prediction success rate, calculated based on the average Female and Male F1 model scores shown in

Figure 13. Additionally, the emotion and age range correspondence analysis shown in Figure 15 can be incorporated with a broader perspective into the correlation analysis in Tables 8 and 9. This integration would allow the development of a predictive model focused on the impact of age-related unemployment and its emotional reflections. When we finally compare the model which we used in this study with studies above, our 76% accuracy rate of DeepFace is considerably higher compared to the transfer learning model by Sabri and El-Bakry, but it falls short of Levi and Hassner's gender prediction accuracy of 86%. In this context, DeepFace offers broader and more balanced accuracy, whereas Levi and Hassner's model stands out as more successful specifically in gender prediction.

2. Methodology and Results

Face structures from street interviews are identified in this work using Python's OpenCV module and Deep Face package. Comparative with unemployment statistics, statistical analyses assess model accuracy, prediction, and consistency. The paper also looks at how face traits affect emotional states, gender, and age. Using F1 score, accuracy, and recall criteria, the paper assessed the expected accuracy of the model by contrasting actual gender values with expected ones. To evaluate model performance, a chi- square analysis was done on the correlations among categorical variables—more especially, gender, age, emotion.

By means of correspondence analysis, the study investigated data structures and relationships among variables, therefore clarifying their links. Using a non-parametric correlation approach, it contrasted negative emotions from OpenCV and DeepFace libraries with unemployment rates. Based on interviews posted on social media over years, the study concentrated on sociological and psychological issues pertinent to daily living.

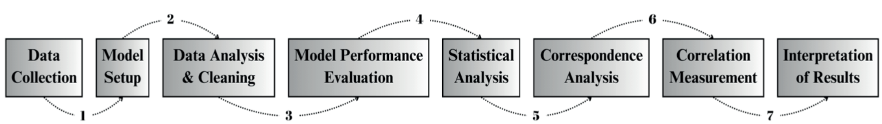

Figure 1: Summarized Workflow for This Study

2.1. Recognizing the Core Ideas of the Model Type

In this section, we defined and investigated the fundamentals of our code architecture.

2.1.1. Importing the Libraries

With the OpenCV library being the main choice, the Python programming environment was utilized in the data collection phase for its wide range of libraries fit for visual analysis (GitHub, n.d.). Figure 2 shows that at the start of the working process, the necessary libraries were imported into the program environment.

```
import cv2
from deepface import DeepFace
import os
import pandas as pd
```

Figure 2: Python Code of Essential Libraries for the Software

OpenCV, or cv2: a Python tool for image processing.

Deep Face is a Python tool for facial detection and analysis.

os: An operating system function execution library.

Pandas: a broad Python tool for data manipulation and analysis.

2.1.2. Model Importation

Using a pre-trained facial recognition model (shown in Figure 3) along with Python's facilities, one may ensure exact results from visual data. Using this model was meant to improve data acquisition accuracy.

The next phase will be visual example assessment of the prediction accuracy of the model.

```
face_cascade = cv2.CascadeClassifier('dosya_yolu.xml')
```

Figure 3: Python Code of Integrating the Model into the System

2.1.3. Output Storage

A Pandas DataFrame was established to store the results, as illustrated in Figure 4.

```
result_df = pd.DataFrame(columns=[
    'YEAR', 'ORDER', 'FEMALE PREDICTION RATE', 'MALE PREDICTION RATE',
    'ANGRY RATE', 'DISGUST RATE', 'FEAR RATE', 'HAPPY RATE',
    'SAD RATE', 'SURPRISE RATE', 'NEUTRAL RATE',
    'DOMINANT GENDER', 'DOMINANT EMOTION', 'AGE PREDICTION'
])
```

Figure 4: Python Code of Transferred Variables to the Data Frame

2.1.4. Importing the Image

The import process was carried out with the code shown in Figure 5; the directory of all images for analysis was set aside.

```
image_folder = '/path/to/your/image/folder/'
image_files = os.listdir(image_folder)
```

Figure 5: Python Code of Importing Visual Content

2.1.5. Visual Data Manipulation

As Figure 6 shows, a loop was developed to handle every image file (Tekin, M. (n.d.)).

```
for image_file in image_files:
    if image_file.endswith('.png'):
```

Figure 6: Python Code of Processing Cycle

The photos in color format were loaded in line with the year using the code in Figure 7.

```
yil, sira = image_file.split('.')[0].split('-')
yil, sira = int(yil), int(sira)

input_image = cv2.imread(os.path.join(image_folder, image_file))
```

Figure 7: Python Code of Color Loading by Year

2.1.6. Grayscale Technique for Face Detection

I found faces in the pictures using the OpenCV package's detectMultiScale() technique. This system uses a multi-scale approach and grayscale photo processing to improve speed and lower computational requirements (Tekin, M. (n.d.).

```
faces = face_cascade.detectMultiScale(
    gray,
    scaleFactor=1.1,
    minNeighbors=5,
    minSize=(30, 30)
)
```

Figure 8: Python Code of Grayscale Methodology

2.1.7. Outputs for Variable Extraction Using DeepFace

After detecting the faces, we used the Deep Face library to evaluate the gender, age, and emotions of every found face. These variables are extracted using the following code:

```
result_emotion = DeepFace.analyze(input_image, actions=['emotion'])
result_age = DeepFace.analyze(input_image, actions=['age'])
result_gender = DeepFace.analyze(input_image, actions=['gender'])
```

Figure 9: Python Code of Variable Extraction Utilizing DeepFace

2.1.8. The Fundamental Mathematical Framework

DeepFace uses advanced deep learning techniques to perform facial recognition, evaluating attributes like age, gender, and emotional expression. It classifies emotions based on facial features and accurately estimates age and gender.

2.1.9. The Underlying Mathematical Framework

The foundation of Deep Face's approach is Convolutional Neural Network (CNN) application. The model extracts many components at different levels -including edges, textures, and complex patterns- as an input image passes several convolutional layers which are showed in Figure 10 (Kaur, G., & Kaur, P. (2020)). The obtained features are arranged into feature maps that, with each next layer, record even more intricate properties.

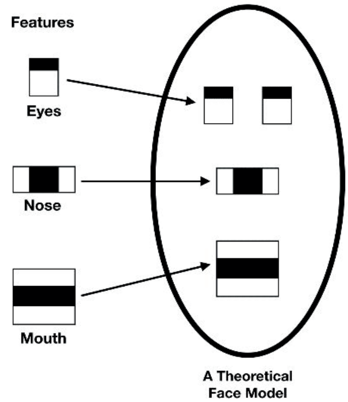

Figure 10: HAAR Face Detection Sample

2.2. Accuracy of Model Predictions on Gender Variable

Understanding accuracy and success rates helps one evaluate machine learning models by means of real-world data comparison of model prediction accuracy versus. These steps show whether a model can provide accurate projections in relevant contexts for making decisions. Development of models depends on improvement and modification; they assist to pinpoint areas that need work and help to avoid false positives and false negatives. Model success rates measure the quality of a dataset, and if a model underperforms, it requires close examination for potential flaws or errors. Several metrics are used to compare and compare the performance of various models, identifying the model with the best results.

2.3. Confusion Matrix

Examining the dependent variables in the dataset usually helps one to estimate successful predictions from our model using classification algorithms by means of accuracy rates. In this case, the performance measures of the model were calculated solely depending on the Gender variable without considering any dependent or independent variables (Encord. (n.d.)).

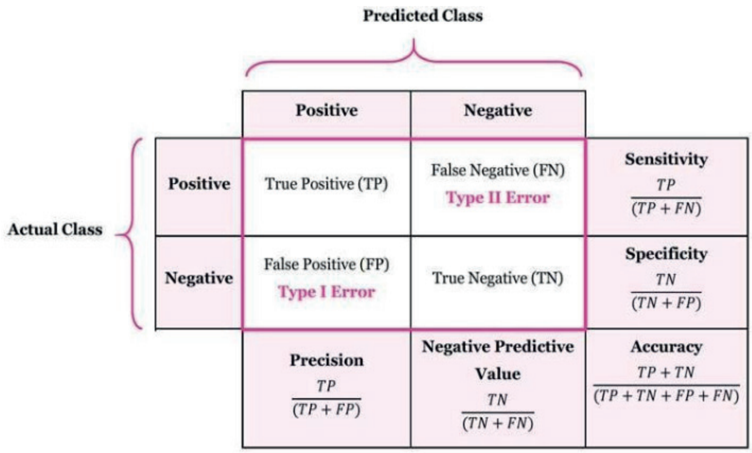

Figure 11: Details of the Confusion Matrix

2.3.1. Components of the Confusion Matrix

2.3.1.1. True Positive (TP)

This indicates cases when the model correctly recognized the positive class. The model fairly projected a positive class; the actual class was positive. For example; A real positive results from a medical test correctly identifying a patient with an ailment.

2.3.1.2. False Positive (FP)

This happens when the model misfits the positive class. Although the model labeled it as positive, the actual class was negative. Sometimes this is referred to as a "type I error". For example; A false positive in medicine is the result of a test suggesting, mistakenly, that a healthy person has a disease.

2.3.1.3. True Negative (TN)

This happens when the model correctly spots the negative class. The true class is negative as is the prediction of the model. A real negative would be the outcome of a medical test, for example, if it correctly marks a healthy patient as free of the condition.

2.3.1.4. False Negative (FN)

False negative transpires when the model mistakenly forecasts the negative class. Though the model assigned it as negative, the actual class was positive. We call this a "type II error." For example, this happens when a medical test misses an ill patient, so falsely suggesting that they are healthy.

2.3.2. Performance Metrics Obtained from the Confusion Matrix

In this section of the study, the focus is on calculating model score metrics.

2.3.2.1. Sensitivity (Recall or True Positive Rate)

This assesses the model's capacity to accurately detect positive instances. It is computed as:

$$Sensitivity = \frac{TP}{TP + FN} \tag{1}$$

Sensitivity equals true positives divided by the sum of true positives and false negatives. High sensitivity indicates that the model accurately detects true positive cases.

2.3.2.2. Specificity

Specificity is defined as TN divided by the sum of TN and FP.

$$Specificity = \frac{TN}{TN + FP} \tag{2}$$

High specificity indicates that the model excels at identifying real negatives

2.3.2.3. Precision (Positive Predictive Value)

Precision denotes the proportion of projected positive situations that are genuinely positive. Precision is computed as:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

High precision indicates that when the model predicts a positive class, it is typically accurate.

2.3.2.4. Negative Predictive Value (NPV)

This measure reflects the proportion of projected negative situations that are genuinely negative. It is computed as:

$$NPV = \frac{TN}{TN + FN} \tag{4}$$

A high NPV indicates that when the model forecasts a negative class, it is typically precise.

2.3.2.5. Accuracy

Accuracy quantifies the overall correctness of a model's predictions, indicating the ratio of true results (including both true positives and true negatives) to the total number of forecasts. Accuracy is computed as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

The high accuracy indicates that the model effectively identifies both positive and negative cases accurately.

Each statistic offers a distinct viewpoint on the model's performance, facilitating the assessment of its strengths and limitations in prediction accuracy.

2.3.3. Illustration of a Confusion Matrix Utilizing Our Data

The objective observability of the gender variable for this evaluation drives much of the choice of it. Unlike emotions or age, which depend on the subjective interpretation of the researcher, gender may be ascertained scientifically, therefore guaranteeing more accurate and significant findings. Figure 12 exemplifies the matrix comprising the parameter values for assessing the performance of any model.

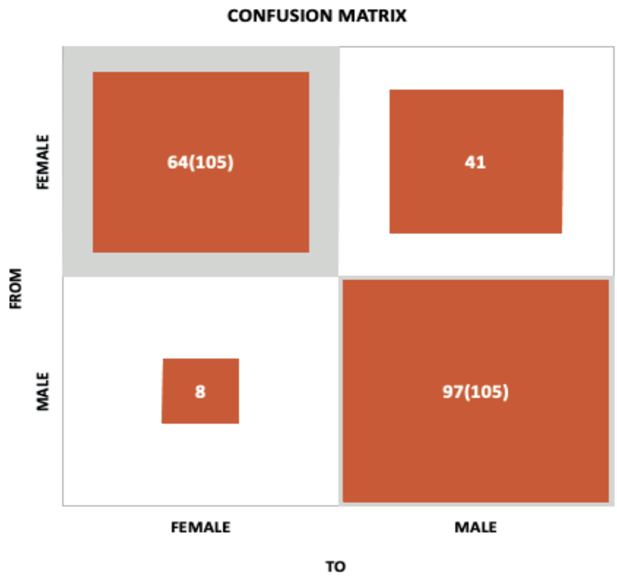

Figure 12: Sample Confusion Matrix for Gender

Analyzing distinct Precision and Recall metrics for the “FEMALE” and “MALE” categories in a gender prediction model facilitates a more comprehensive assessment of the algorithm’s efficacy for each class. Furthermore, juxtaposing the F1-Scores for both groups facilitates a more substantive study. The model’s success rates, derived from the data in Figure 12, produced the confusion matrix shown in Figure 11 (Chakravorty, D. (n.d.)). A comparative analysis of both male and female categories has been conducted using bar charts on the subsequent page.

2.3.3.1. Model Accurate Metrics

Figure 13 below presents the comparative success rates for cases in which the positive condition is evaluated for both males and females.

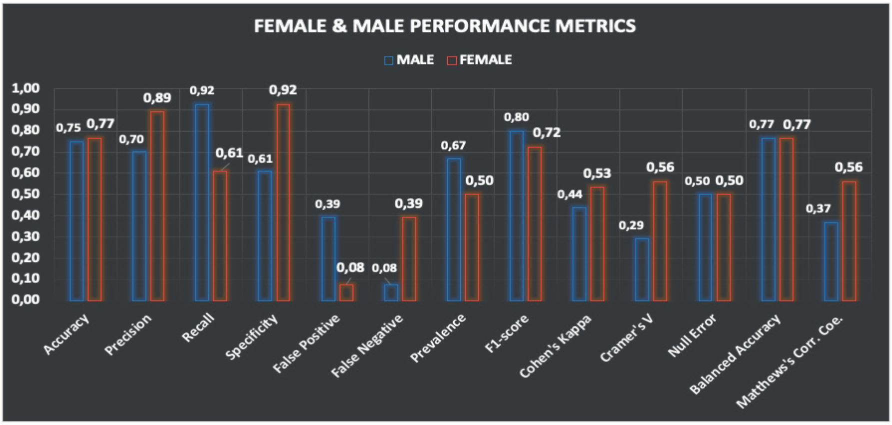

Figure 13: Comparative Analysis of Model Performance Metrics

While each measurement parameter is crucial, the overall efficacy of a model's predictions derived from observational data is more accurately assessed using the F1 score.

The comparison of the F1 score values reveals that F1-Score for Female = 0.72 is less than F1-Score for Male = 0.80, indicating superior predictive capability for males over females by the model. Consequently, in test groups when the positive condition applies to both genders, the model demonstrates superior efficacy in predicting males compared to girls.

2.4. Comprehending the Interconnections Among Categorical Variables

The Chi-Square ($\chi 2$) test is a non-parametric statistical method utilized to analyze the association between categorical variables. Analogous to parametric hypothesis testing, the aim is to formulate a hypothesis and ascertain its potential rejection.

The Chi-Square distribution, similar to the t-distribution, possesses only one degree of freedom. Generally, at lower degrees of freedom, the Chi-Square distribution exhibits right skewness. As the degrees of freedom rise, the Chi-Square distribution increasingly resembles the shape of a normal distribution curve.

2.4.1. Chi-Square Independence Test

The Chi-Square Independence Test assesses the independence or relationship between variables organized in 2x2 or rxc contingency tables.

This test is utilized to analyze relationships between qualitative (non-numerical) factors present in cross-tabulations (contingency tables).

The Pearson Chi-Square test, Yates' corrected Chi-Square test, and Fisher's exact test are applicable for 2x2 tables. The Pearson Chi-Square test is utilized for rxc tables. The degrees of freedom are determined by the formula (r-1) x (c-1), where r denotes the number of rows and c is the number of columns (Çorba, B. Ş. (n.d.)).

The hypotheses for the test are as follows:

H_0: The variables are independent (there is no relationship between the variables).

H_1: The variables are not independent (there is a relationship between the variables).

Row	Column		Total
	C1	C2	
R1	A A'	B B'	N1=A+B
R2	C C'	D D'	N2=C+D
Total	N3=A+C	N4=B+D	N

Figure 14: Illustrative Chi-Square (Contingency) Table

$$\chi^2 = N\sum_{i=1}^{I}\sum_{j=1}^{J}\frac{\left(n_{ij}-e_{ij}\right)^2}{e_{ij}} \tag{6}$$

In this context, n_{ij} represents the observed frequencies (A, B, C, D), while e_{ij} (A', B', C', D') symbolizes the predicted frequencies. The anticipated frequencies are calculated by multiplying the respective row and column totals and thereafter dividing by the grand total. If $\chi^2 \leq \chi^2_{\alpha,df}$ or $p>0.05$, the null hypothesis (H_0) cannot be rejected. indicating that there is no significant difference between observed and expected frequencies. Otherwise, the null hypothesis is rejected, implying a significant difference.

2.4.1.1. Relationship Between Gender and Emotional Response

At this juncture, the correlation between the two variables was analyzed utilizing the Chi-Square test. Due to certain cells in the contingency Figure 14, Fisher's Exact test statistics were utilized.

Hypotheses:

H_0: There is no significant relationship between gender and the response given to the question asked or the problem presented in the street interviews.

H_1: There is a significant relationship between gender and the response given to the question asked or the problem presented in the street interviews.

Table 1: SPSS Output of Gender & Sentimental Reaction Crosstab

GENDER & SENTIMENTAL REACTION CROSSTAB

			SENTIMENTAL REACTION						
			Happy	Sad	Fear	Angry	Neutral	Disgust	Total
GENDER	Male	Count	16	33	9	9	29	1	97
		Expected Count	20.5	33.7	10.8	6.0	25.3	.6	97.0
	Female	Count	18	23	9	1	13	0	64
		Expected Count	13.5	22.3	7.2	4.0	16.7	.4	64.0
Total		Count	34	56	18	10	42	1	161
		Expected Count	34.0	56.0	18.0	10.0	42.0	1.0	161.0

As the cells in the cross-table shown in Table 1 exhibit values below 5 for both observed and expected frequencies, deriving conclusions from the Chi-Square statistics in Table 2 may diminish the model's significance. Consequently, it is essential to consult the statistics derived by Fisher's Exact test.

Table 2: SPSS Output of Gender & Sentimental Reaction Chi-Square Statistics

Chi-Square Statistics (χ2) For Gender & Sentimental Reaction

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)	Point Probability
Pearson Chi-Square	9.013	5	.109	.092		
Likelihood Ratio	10.100	5	.072	.077		
Fisher's Exact Test	8.919			.091		
Linear-by-Linear Association	5.012	1	.025	.027	.014	.003

Table 2 indicates that the p-value from Fisher's Exact Test statistic above the alpha threshold of 0.05. Consequently, we are unable to dismiss the null hypothesis (H_0). No substantial correlation was identified between Gender and Emotional Response. Nonetheless, this is not invariably true, as outcomes may fluctuate based on the quantity of observations in our dataset.

2.4.1.2. Gender & Response Tendency Relationship

To assess the correlation between gender and emotion from an alternative viewpoint, and to reduce errors by ensuring that the observed and expected values in the cells surpass 5, the responses (i.e., emotions) were categorized into positive, negative, and neutral emotional states and analyzed from a tendency perspective.

In this instance, our revised hypotheses should be articulated as follows:

H_0: There is no significant relationship between gender and the tendency of the response given to the question asked or the problem presented in the street interviews.

H_1: There is a significant relationship between gender and the tendency of the response given to the question asked or the problem presented in the street interviews.

Table 3: SPSS Output of Gender & Reaction Tendency Crosstab

GENDER & REACTION TENDENCY CROSSTAB

			REACTION TENDENCY			
			Positive Reaction	Negative Reaction	No Reactio	Total
GENDER	Male	Count	16	52	29	97
		Expected Count	20.5	51.2	25.3	97.0
	Female	Count	18	33	13	64
		Expected Count	13.5	33.8	16.7	64.0
Total		Count	34	85	42	161
		Expected Count	34.0	85.0	42.0	161.0

To get more significant results and minimize errors, we can conclude that there is no substantial correlation between gender and emotional response, as indicated by the statistics in Table 4.

Table 4 indicates that the Pearson Chi-Square statistic, specifically the calculated p-value, is less than the alpha value of 0.05. It can be asserted that there is no substantial correlation between the two categorical variables.

The Pearson Chi-Square Test assesses the statistical significance of the disparity between observed and expected frequencies, whereas the Likelihood Ratio evaluates model fit and identifies the superior model among various alternatives.

Table 4: SPSS Output of Gender & Reaction Tendency Chi-Square Statistics

Chi-Square Statistics (χ2)

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	3.858	2	.145
Likelihood Ratio	3.841	2	.147
Linear-by-Linear Association	3.673	1	.055

2.4.1.3. Age Range & Emotional Response Relationship

The association between the two variables was analyzed using the Chi-Square test at this step. Due to the majority of cells in the contingency table containing values below 5, Fisher's Exact test and Monte Carlo statistics were deemed appropriate.

Hypotheses:

H_0: There is no significant relationship between the age range and the response given to the question asked or the problem presented in the street interviews.

H_1: There is a significant relationship between the age range and the response given to the question asked or the problem presented in the street interviews.

Table 5: SPSS Output of Age Range & Sentimental Reaction Crosstab

AGE_RANGE & SENTIMENTAL REACTION CROSSTAB

			SENTIMENTAL REACTION						
			Happy	Sad	Fear	Angry	Neutral	Disgust	Total
AGE RANGE	20-24	Count	2	4	0	0	1	0	7
		Expected Count	1.5	2.4	.8	.4	1.8	.0	7.0
	25-29	Count	7	9	1	1	12	0	30
		Expected Count	6.3	10.4	3.4	1.9	7.8	.2	30.0
	30-34	Count	18	25	5	3	15	0	66
		Expected Count	13.9	23.0	7.4	4.1	17.2	.4	66.0
	35-39	Count	5	8	8	2	7	0	30
		Expected Count	6.3	10.4	3.4	1.9	7.8	.2	30.0
	40-44	Count	1	4	1	2	6	0	14
		Expected Count	3.0	4.9	1.6	.9	3.7	.1	14.0
	45-49	Count	0	6	3	1	1	1	12
		Expected Count	2.5	4.2	1.3	.7	3.1	.1	12.0
	50-54	Count	1	0	0	1	0	0	2
		Expected Count	.4	.7	.2	.1	.5	.0	2.0
Total		Count	34	56	18	10	42	1	161
		Expected Count	34.0	56.0	18.0	10.0	42.0	1.0	161.0

Upon analyzing the Monte Carlo and Fisher's Exact test statistics on the correlation between age range and emotional response in Table 6, it is evident that the p-value is less than the alpha threshold of 0.05. Consequently, we can dismiss the null hypothesis (H_0). Consequently, we may ascertain that a substantial correlation exists between age range and emotional response.

Table 6: SPSS Output of Age Range & Sentimental Reaction Chi-Square Statistics

Chi-Square Statistics (χ2) For Age Range & Sentimental Reaction									
				Monte Carlo Sig. (2-sided)			Monte Carlo Sig. (1-sided)		
					95% Confidence Interval			95% Confidence Interval	
	Value	df	Asymptotic Significance (2-sided)	Significance	Lower Bound	Upper Bound	Significance	Lower Bound	Upper Bound
Pearson Chi-Square	49.797	30	.013	.037	.008	.067			
Likelihood Ratio	42.113	30	.070	.050	.016	.083			
Fisher's Exact Test	42.962			.019	.000	.040			
Linear-by-Linear Association	1.435	1	.231	.267	.199	.335	.130	.078	.182
Monte Carlo Method				.03					

2.4.2. Correspondence Analysis

Correspondence analysis is a statistical method used to study interactions among variables, improving the accuracy of Chi-Square independence tests and enhancing awareness of links among categorical variables. It is essentially Principal Component Analysis (PCA), translating high-dimensional contingency tables into lower-dimensional spaces for better understanding (Medium. (n.d.)).

2.4.2.1. Contingency Table Construction

Start with a contingency table including the two variables' observed frequencies for each other. For two categorical variables, for example, the table would show the frequency of every category combination. Estimating Anticipated Frequencies.

2.4.2.2. Calculating Expected Frequencies

From the total count N of all observations in the table, calculate the proportion of each cell relative to the total. This gives us the relative frequency matrix, where each entry $\boldsymbol{P_{ij}}$ is simply $\boldsymbol{P_{ij}} = \frac{\boldsymbol{n_{ij}}}{\boldsymbol{N}}$, with $\boldsymbol{n_{ij}}$ being the count in cell $(\boldsymbol{i}, \boldsymbol{j})$. This step helps us understand how frequently each combination occurs compared to the whole dataset (Michael. (n.d.)).

2.4.2.3. Determining Marginal Totals

Calculate row totals r_i and column totals $\boldsymbol{c_j}$, which tell us the overall distribution of each category. These totals are essential for understanding how much each category contributes overall (Greenacre, M., & Blasius, J. (2006)).

2.4.2.4. Calculating Expected Frequencies

The expected frequency for each cell $\boldsymbol{e_{ij}}$ is found by multiplying the corresponding row total by the column total and dividing by the grand total N:

$$e_{ij} = \frac{n_{i.} \,.\, n_{.j}}{N} \tag{7}$$

This tells us what we would expect to see if there were no particular relationship between the categories.

2.4.2.5. Measuring Deviations Using Chi-Square

To see how much each cell differs from what's expected, we use the formula:

This statistic measures the overall association between the categories, indicating whether they're independent or related.

$$\chi^2 = N \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{\left(n_{ij} - e_{ij}\right)^2}{e_{ij}} \tag{8}$$

2.4.2.6. Standardizing the Data

Create a matrix of standardized residuals showing the expected frequency's variation from each observed frequency, corrected as follows:

$$S_{ij} = \frac{\left(p_{ij} - m_{ij}\right)}{\sqrt{m_{ij}}} \tag{9}$$

where $\boldsymbol{m_{ij}}$ is the expected probability for cell $(\boldsymbol{i}, \boldsymbol{j})$. This matrix shows the degree of deviation each category combination deviates from what we would anticipate absent a relationship.

2.4.2.7. Singular Value Decomposition (SVD) helps one to break down the Matrix.

Correspondence Analysis's foundation is Singular Value Decomposition (SVD) breaking down this uniform matrix. This mathematical method essentially breaks up our complicated matrix into simpler components:

$$S = U \Sigma V^T \tag{10}$$

- **U** and **V** are matrices containing information about the rows and columns, respectively.
- Σ is a diagonal matrix containing singular values that indicate how much each dimension contributes to the overall structure.

2.4.2.8. Deriving Principal Coordinates

In a low-dimensional space, the SVD results let us determine the coordinates for rows and columns both individually. On a 2D (or 3D) plot, each point denotes a category from the original data and allows one to view these coordinates.

- The row coordinates are calculated as:

$$F_{ij} = \frac{v_{jk} - \sigma_k}{\sqrt{r_i}} \tag{11}$$

- The column coordinates are calculated as:

$$G_{ij} = \frac{v_{jk} - \sigma_k}{\sqrt{c_j}} \tag{12}$$

2.4.2.9. Visualization and Interpretation

Correspondence Analysis generates as points rows (categories from one variable) and columns (categories from another variable). Close proximity of points indicates stronger category similarity or association. This graphical representation helps one to understand the links among the classed variables.

2.4.2.10. Output of Correspondence Analysis on Our Data

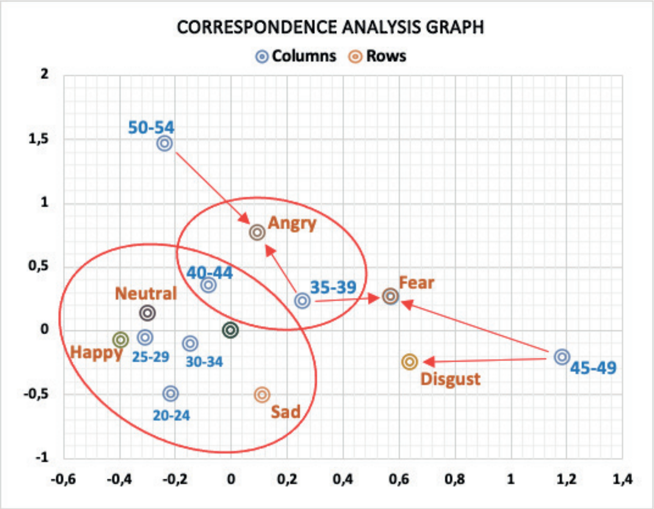

Figure 15: SPSS Correspondence Output Regarding Age Range and Sentimental Reaction

In the Figure 15, the graph of Correspondence Analysis shows the association between several age groups (in blue) and different emotional reactions (in orange).

Clusters and Associations:

Left Cluster: The younger demographics (20–24, 25–29, 30–34) substantially correlate with the emotions “Happy” and “Neutral”. This suggests that those in these age ranges are more likely to show either favorable or indifferent emotional reactions.

The age ranges 40–44 and 35–39 show more clear relationships with emotions like “Sad” and “Angry.” This implies that some age groups could have more frequent feeling or expression of these emotions.

Particularly those between 45 and 49, the older age groups show more congruence with emotions like “Fear” and “Disgust”.

Demographic Cohorts and Affective Trends:

The age range 50–54 indicates more varied or less predictable emotional reactions since their age range shows no clear correlation with any one emotion.

Located centrally, the 35–39 age group seems to be linked with a greater range of emotions, suggesting they could show different emotional reactions.

Closeness and Significance:

On the graph, points that are closer together indicate a stronger association. Younger age groups who show closeness to "Happy" show a clear predisposition for positive feelings.

On the other hand, the gap between "Fear" and the younger age groups points to less common similar emotions in these populations.

Comprehensive Analysis:

This graph shows clearly how age affects emotional reactions. People between the ages of 20 and 34 prefer either pleasant or neutral feelings; individuals between the ages of 45 and older show an inclination for emotions like "Fear" and "Disgust." The 35–39 age group shows a harmonic mix of positive and negative emotions.

This study precisely and clearly clarifies the differences in emotional dispositions between several age groups.

2.5. Assessing the Correlation Between Unemployment and Negativity Rate

The initial inquiry that arises is how categorical data, such as emotional responses, may be transformed into numerical data. In summary, a pre-trained facial recognition model and Python libraries were employed to generate predictions indicating the percentage and probability of each emotion for every observation. Consequently, the rates of negative emotions for each observation were aggregated, and this procedure was reiterated for every observation. The aggregate for each case was divided by the total observations for that year, yielding the data for the "Negativity Rate" variable. Table 7 and Formula 13 below offer a comprehensive elucidation.

The emotion with the highest percentage for each observation was deemed the predominant emotion.

Table 7: Annual Negativity Rate Calculation System

$Year$	$Observation$	$R_{(Negativity)i-year}$				$R_{(Positivity)i-year}$	$R_{(Neutrality)i-year}$
		$R_{(Anger)i-year}$	$R_{(Fear)i-year}$	$R_{(Sadness)i-year}$	$R_{(Disgust)i-year}$	$R_{(Happiness)i-year}$	$R_{(Neutral)i-year}$
2017	1	$R_{(Anger)1-2017}$	$R_{(Fear)1-2017}$	$R_{(Sadness)1-2017}$	$R_{(Disgust)1-2017}$	$R_{(Happiness)1-2017}$	$R_{(Neutral)1-2017}$
...	...	...	...	...	...	...	...
2017	n	$R_{(Anger)n-2017}$	$R_{(Fear)n-2017}$	$R_{(Sadness)n-2017}$	$R_{(Disgust)n-2017}$	$R_{(Happiness)n-2017}$	$R_{(Neutral)n-2017}$

The annual negativity rate obtained actually gives us an idea of the tendency and intensity of negative reactions in the facial expressions of individuals within that year or calculated period.

$$R_{(Negativity)2017} = \frac{R_{(Negativity)1-2017} + \ldots + R_{(Negativity)n-2017}}{n} \tag{13}$$

Pearson and Spearman correlations were used to measure the relationship between unemployment and the negativity rate. The main reason for using both parametric and non-parametric methods is that we cannot be certain whether both variables follow a normal distribution across the population.

When analyzing a 7-year period from 2017 to 2023, having only 7 observations is not sufficient to confidently determine the relationship between the two variables. Therefore, both parametric and non-parametric methods were applied.

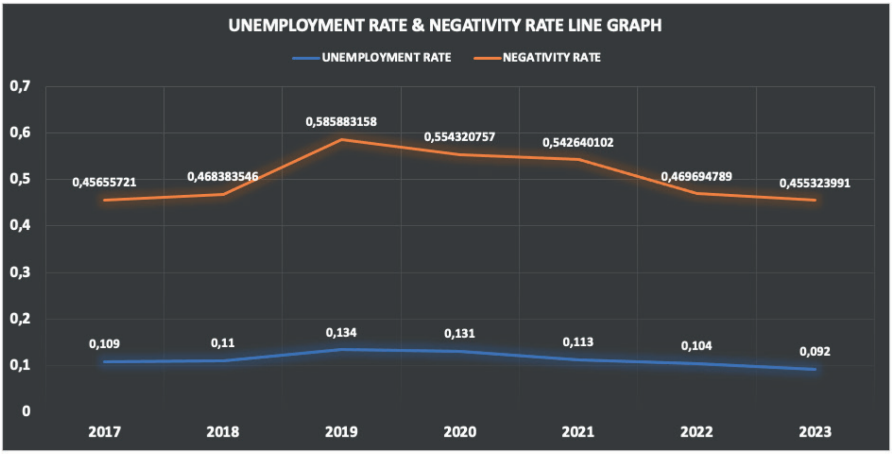

Figure 16: Unemployment & Negativity Rates Line Graph by Years

In Figure 16, we can say that both variables exhibit similar curves. However, there are also important breaking points present, and the resulting graphs may show variations when working with a larger data set.

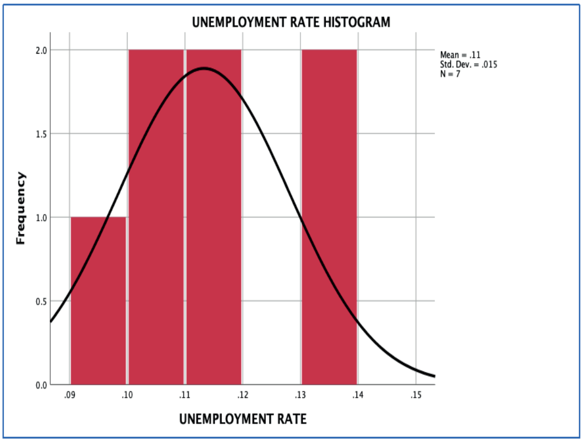

Figure 17: Normal Skew & Histogram of Unemployment Rate

The normality curves of both variables are shown in Tables 15 and 16, respectively. To confirm whether they follow a normal distribution, more comprehensive statistics would be needed. However, since the number of observations we have is reduced to 7 on an annual basis, this limited sample size affects the choice of tests and parameters, potentially reducing the reliability of the analysis.

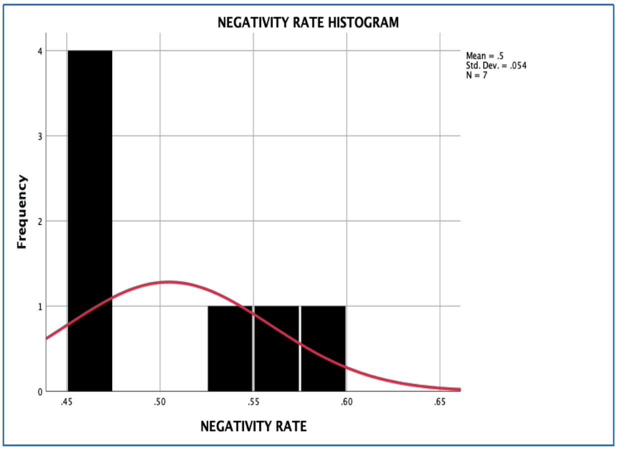

Figure 18: Normal Skew & Histogram of Negativity Rate

The normality curves of both variables are shown in Figure 17 and 18, respectively. To confirm whether they follow a normal distribution, more comprehensive statistics would be needed. However, since the number of observations we have is reduced to 7 on an annual basis, this limited sample size affects the choice of tests and parameters, potentially reducing the reliability of the analysis.

When we try to understand the relationship between two numerical variables, we need to look at the distributions of the variables. After measuring the distributions of them, we can calculate the correlations between them based on the distributions. However, with small data sets, if we cannot predict the distributions of the variables, we can perform measurements under both parametric and non-parametric assumptions to make comparisons. Still, knowing the distribution while interpreting the results would increase the accuracy of the outcomes.

2.5.1. Pearson's Correlation Coefficient

The Pearson correlation coefficient quantifies the degree and direction of the linear association between two continuous variables. It presupposes that both variables follow a normal distribution and that their connection is linear. The Pearson coefficient varies between -1 and +1 (Technology Networks. (n.d.)).

- A number of +1 signifies an ideal positive linear correlation.
- A value of -1 denotes an ideal negative linear correlation.
- A value around 0 implies the absence of a linear correlation.

The equation for the Pearson correlation is:

$$r=\frac{\Sigma\left(X_{\acute{Y}}-\bar{X}\right)\left(Y_i-\bar{X}\right)}{\sqrt{\Sigma\left(X_i-\bar{X}\right)^2\left(Y_i-\bar{Y}\right)^2}} \tag{14}$$

Where:

$\boldsymbol{X}_i$ and $\boldsymbol{Y}_i$ are individual data points,

$\bar{\boldsymbol{X}}$ and $\bar{\boldsymbol{Y}}$ are the means of $\boldsymbol{X}$ and $\boldsymbol{Y}$, respectively.

The Pearson approach is most effective with data that satisfies normality criteria and has a linear connection between variables.

2.5.2. Spearman's Rank Correlation Coefficient

The Spearman rank correlation coefficient is a non-parametric metric employed to evaluate the strength and direction of the association between two variables. In contrast to Pearson, it does not necessitate regularly distributed data and instead assesses the monotonic relationship between variables. It is optimal for handling ordinal data or when the assumptions of normalcy are violated.

Spearman operates by ordering the values of each variable and subsequently computing Pearson's correlation based on these ranks. It also spans from -1 to +1:

A value of +1 signifies an ideal positive monotonic correlation. A value of -1 signifies an ideal negative monotonic correlation. A value around 0 indicates the absence of a monotonic connection (Statstutor. (n.d.)).

$$\rho = 1 - \frac{6\sum d_i^2}{n\left(n^2 - 1\right)} \tag{15}$$

Where:

- d_i is the difference between the ranks of corresponding values of X and Y
- n is the number of data points

2.5.3. Pearson & Spearmen Correlation Comparison on Negativity & Unemployment Rates

Assuming that both variables come from populations with a normal distribution, we used the Pearson correlation measure. As seen in Table 8, the results indicate that there is a strong relationship between the two variables. According to this assumption, the degree of correlation is approximately 88%.

Table 8: SPSS Output of Pearson Correlation Value Between Negativity & Unemployment Rates

PARAMETRIC CORRELATION MATRIX			
		UNEMPLOYMENT RATE	NEGATIVITY RATE
UNEMPLOYMENT RATE	Pearson Correlation	1	.880
	Significance		.004
NEGATIVITY RATE	Pearson Correlation	.880	1
	Significance	.004	

When assuming that both variables come from populations that do not follow a normal distribution, a nonparametric correlation method should be preferred. In this context, the Spearman rank correlation coefficient was calculated. The correlation degree obtained under this assumption is quite high, similar to the parametric measure. Under this assumption, the relationship between the two variables was measured at approximately 89%.

Table 9: SPSS Output of Spearmen Correlation Value Between Negativity & Unemployment Rates

NONPARAMETRIC CORRELATION MATRIX			UNEMPLOYMENT RATE	NEGATIVITY RATE
Spearmen's Rho	UNEMPLOYMENT RATE	Correlation Coefficient	1.000	.893
		Significance		.003
	NEGATIVITY RATE	Correlation Coefficient	.893	1.000
		Significance	.003	

3. Conclusion and Discussion

The age, gender, and emotional reactions of people shown in street interviews uploaded on YouTube were examined in this paper using artificial intelligence and facial recognition technologies. Examining the possible relationship between people's answers to questions regarding the economy and unemployment and the unemployment rates was the major objective of the study

First, using Python-based facial recognition technologies (OpenCV and DeepFace), data on age, gender, and emotions was gathered via street interviews carried out between 2017 and 2021 in the first phase of the research. At this point the dataset included the estimated age, gender, and emotional responses gleaned from people's facial expressions.

We assessed the model's performance in the next phase. The accuracy level of the model was investigated utilizing performance criteria including F1 score, accuracy, and recall by means of a comparison between the expected and actual gender data). Using statistical approaches including the Chi-Square independence test and Pearson and Spearman correlation analysis, the relationship between gender and age groups and their emotional responses was also examined. The obtained emotional reactions were evaluated yearly, particularly with relation to negative emotions, and computed as a "negativity rate".

In the next phases, more thorough analysis of the link between gender and age groups and emotional reactions was investigated. By now the associations between categorical variables could be seen using correspondence analysis, and notable links were found. Younger age groups were more related with "happy" and "neutral" emotions, middle age groups were linked with "sad" and “angry” emotions, while older age groups were linked with emotions such “fear” and “disgust,” it was noted.

The study discovered a clear relationship between changes in unemployment rates and unpleasant emotions on individuals’ facial expressions. This implies that one can examine personal demographic characteristics and emotional reactions using facial recognition technologies and artificial intelligence. The study implies that these instruments can provide better knowledge of human reactions by helping to grasp the interplay between personal emotions and economic variables, thereby enabling further research in social sciences, economics, and marketing.

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