MALAYSIAN JOURNAL OF COMPUTING AND APPLIED MATHEMATICS (2020) 3 (2) 60-72

DOI: *https://doi.org/10.37231/myjcam.2020.3.2.45*

Article: Received 11.09.2020; Accepted 07.12.2020; Published 23.12.2020

NAÏVE BAYES EMOTION CLASSIFICATION OF FINAL STATEMENTS FROM DEATH ROW YOUTHS BEFORE EXECUTION

Jamilu Awwalu[a, ✉], Saleh El-Yakub Abdullahi[b], Ogwueleka Francisca Nonyelum[c]

[a,c]Department of Computer Science, Nigerian Defence Academy, Kaduna, Nigeria
[b]Department of Computer Science, Nile University of Nigeria, Abuja, Nigeria
✉awachi.jami@nda.edu.ng

Abstract: The behaviours of most Death Row inmates in pre-prison era typically involve neurological insult, developmental histories of trauma, family disruption, and substance abuse. These behaviours lead them to commit crimes that finally land them into death row in prison. Rates of psychological disorder among death row inmates are high, where environments and conditions of confinement appear to aggravate such disorders. The last statements of Death row inmates can be deeply emotional. Several Machine Learning (ML) algorithms can be used to classify these emotions. Although simple, the Naïve Bayes algorithm is a popular algorithm that has proven to be robust in text mining. In this study, the Naïve Bayes and benchmark data available from the Texas Department of Criminal Justice to detect and classify emotions from the lasts statements of youth executed on death row. Friedman's test with Bonferroni Adjustment was employed to examine whether the executed inmate's ethnic race has an effect on the emotion of their final statement. Findings from the study indicated that despite 'anger' having both highest minimum and maximum values compared to other emotions, it did not achieve the highest mean score and it came second to the emotion 'joy'. Joy has 0.31 mean score followed by anger with 0.30, sad with 0.26, love with 0.06, fear with 0.05, and surprise with 0.02. Using the Friedman's test with Bonferroni adjustment, this study discovered that there was no significant difference between the different ethnic races of executed inmates and emotions from their last statements.

Keywords: *Naïve Bayes, Emotion Classification, Sentiment Analysis, Youth, Death Row*.

1. INTRODUCTION

Sentiment analysis is an important activity that is applicable through different domains ranging from security (Jurek et al. 2014), politics (Awwalu et al. 2015), to businesses (Al-Kharusi et al. 2015). It mainly focusses on the polarity of people's opinions on positivity, negativity and at times neutrality. However, it does not focus on emotions that lead to such sentiments, these emotions includes; sadness, anger, fear, joy, surprise, and love. Emotions can be detected not only from texts but also from pictures, moving or static.

The final words before death is fascinating and have been collected for a long time in writing for a very long time as it offers researchers insights on how people cope with imminent threats such as death (Hirschmüller and Egloff, 2016). This is no different for death row inmates at point of execution. They are given the chance to make final statements before executed. Death row inmates can be very emotional as execution nears, and studies have been conducted on identifying emotions from their last statements.

The Naïve Bayes algorithm is a probabilistic classifier that is widely used in Machine Learning classification tasks. It is fast and works with degree of certainty as commonly known in probability or with any probabilistic models.

1.1 Background of Study

The behaviours of Death Row inmates in pre prison era involve neurological insult, developmental histories of trauma, family disruption, and substance abuse. These behaviours lead them to commit crimes that finally land them into death row in prison. Rates of psychological disorder among death row inmates are high, where environments and conditions of confinement appear to aggravate such disorders. The last statements of Death row inmates can be deeply emotional.

In this study the Naïve Bayes and benchmark data available from the Texas Department of Criminal Justice website is used to detect and classify emotions from the lasts statements of youth executed on death row inmates. There are different definitions for the age range of youths. According to UNESCO, the age range of youth is between 15 to 25 years (UNDESA, 2014) the African Union define the age range from 15 to 35 years (African Youth Charther, 2014). For our age range definition of youths, 32 years and less age is used so as to have enough data for the study. Also use Friedman's test is used to conduct statistical analysis of results obtained from our emotion classification.

As stated by Boccaccini and Brodsky (2002), rates of psychological disorder among death row inmates are high, where environments and conditions of confinement appear to aggravate such disorders. Contrary to negative emotions that can result from such disorders, a study by Hirschmüller and Egloff (2016) found positive emotional language in final words of the executed. This study aims to find out emotions from the youths executed and how their emotions vary across their different ethnic races.

1.2 Aims and Importance of Study

This study aims to find out emotions from the youths executed and how their emotions vary across their different ethnic races. The objectives are:

i. Classify executed youth inmates emotions from their last statements using Naïve Bayes algorithm and unigram and bigram bag of words (BOW)
ii. Statistically analyze the following using Friedman's test and Bonferroni adjustment
    a. Distribution of their emotions
    b. Discover how their emotions vary based on their ethnic race.

This study can be used by the following:

i. Government and Decision Makers: They can use it to find out the feelings of executed inmates in terms of remorse or otherwise. And also to find out how best they can improve judgment delivery.
ii. Psychologists: Psychology researchers can use this research to link up emotions of the dying executed person last statements and that of a suicidal person. They can also use the correlation between the two to identify possible suicidal person.

1.3 Scope of Study

This work is limited to youths of 35 years and below which are around 36.76% of the total number of executed inmates from the Texas Department of Justice. This means a larger number of executed inmates were not taken into account of this study. Also, other data sources of executed inmates' final words were not considered for this research. As such it cannot be generalized for executed inmates everywhere.

This work is scoped to the following:

i. Data: Executed youths aged 35 and less inmates' last statement from the Texas Department of Justice. 200 youths that fall within the age range were executed from 1982 to June 2017. 126 were selected for this study, out of which 25 declined to make final statements. Therefore the statements collected are from 101 executed inmates.
ii. Classification approach: Combination of Naïve Bayes and unigram, bigram bag of words.
iii. Statistical analysis: Friedman's test with Bonferroni adjustment.

2. LITERATURE REVIEW

Opinion Mining or Sentiment Analysis according to Medhat et al. (2014) is the computational study of people's attitudes, opinions, and emotions toward an entity which could be individuals, topics or events. In most cases, it's off the shelve software implementation is to find out positivity or negativity of opinions or people (Calefato et al. 2017) rather than finding specific emotions of people about a subject matter. This does not mean sentiment analysis does not cover emotions, it actually does. Just that in most of it implementations focus is given to positivity, neutrality, or negativity of people's opinions.

2.1 Different Source for Emotion Recognition

Several works have been done on emotion detection and classification. Emotion classification can be done in different ways, because emotions come from different sources. A work by Kwon et al. (2003) recognized and classified emotions from speech signals. A related work by Kim and André (2006) recognized emotions using physiological and speech signal in short-term observation. Emotions have also been recognized from images as done by Joshi et al. (2011) and Chen et al. (2015). Emotion detection can be implemented using Machine Learning (ML) approach, Semantic approach, or the two approaches combined (Medhat et al., 2014).

2.2 Emotion Detection from Text

The Naïve Bayes algorithm is a popular classifier for emotion classification. It has been used on Music lyric as text by researchers to detect or classify emotions. A study by et al. (2017) crawl the music lyrics and their labels from a popular website named Baidu music and make our four different datasets to automatically classification of Chinese music emotions more effective, used the lyrics of music to analysis and classify music based on emotion. Emotion labels for their work were depression, contentment, and exuberance. Similar study on music text from Turkish songs was conducted also using the Naïve Bayes algorithm by (Durahim et al, 2010). The different areas where the Naïve Bayes has been applied in text mining are shown in Table 1.

A study by Spasić et al. (2012) classified sentences in suicide notes using a scheme of 15 topics, based on lexico–semantic properties of individual words in addition to regular expressions used to represent patterns of word usage across different topics. They trained a naïve Bayes classifier using the features extracted from the training data consisting of 600 manually annotated suicide notes.

Another study to this one by Hirschmüller and Egloff (2016) on positive emotional language in final words by execution on the same dataset source as this study finds a tuning in to emotional positivity in death row inmates' last statements using quantitative text analysis as a method. The study which used the complete dataset at the time it was conducted discovered focused on basics of emotions only which are positivity and negativity out of which they found the executed inmates last statement emotionally tuning to positivity.

Table 1. Naive Bayes Emotion Classification Related Work

Authors	**Research Domain**
Binali et al. (2010)	Emotion detection in text
Avetisyan et al. (2016)	Algorithms for emotion classification
An et al. (2017)	Music emotion classification
Jang et al. (2014)	Bio-signals emotion recognition
Spasić et al. (2012)	Classifying topics in suicidal notes

Several classifiers have been built using the Naïve Bayes algorithm as identified in this study. These studies as identified in this section includes Naïve Bayes algorithm to classify emotions in music, bio-signal, and suicidal notes. Previous studies such as Hirschmüller and Egloff (2016) based their emotion tuning to positivity or negativity only. However, the inmates last statements emotions classification go can be extended to be more clear and detailed beyond just positivity or negativity, such as Joy, Anger, Fear, Love, Surprise, and Fear. Also observing the previous study, it covered all last statements by the executed inmates. However, it can be focused on youth their ethnic races to observe differences if any in the different emotions classified from their last statements.

3. METHODOLOGY

This section discusses the methods used in implementing this study. This involves processes of data acquisition, experiments, and statistical analysis of results obtained from the experiments. As the emotion classification in this study a data mining task, the Cross Industry Standard Platform for Data Mining (CRISP-DM) would be used as the data mining methodology for this study. The CRISP-DM is a hierarchical model that consists of six phases of process model (Wirth, 2000) that is widely used as the methodology for developing Data Mining (DM) and Knowledge Discovery (KD) projects(Marbá et al, 2009). Figure 1 shows the six phases of CRISP-DM.

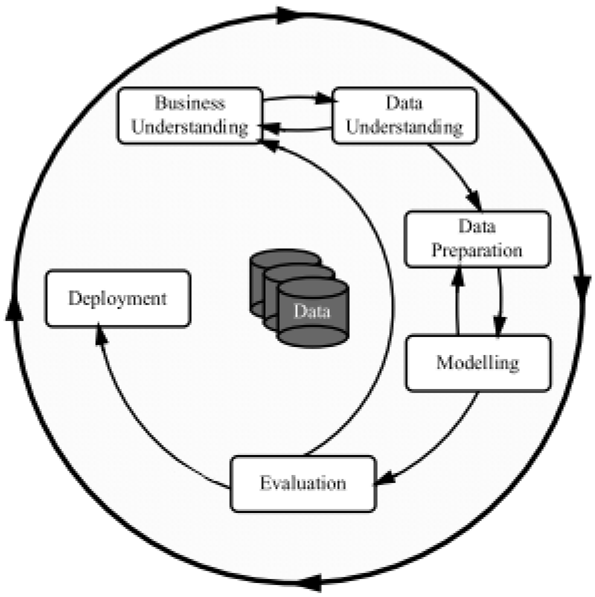

Figure 1. Phases of the CRISP-DM Model, (Chapman et al., 1999).

3.1 Business Understanding

This is the first phase of the CRISP-DM, it focuses on understanding objectives and requirements, then converting this knowledge into a data mining problem definition with a plan designed to achieve the understood objectives. The data mining problem definition for this study is to:

i. Classify executed youth inmates emotions from their last statements.
    a. Plan in emotion classification: Use Naïve Bayes algorithm and unigram and bigram bag of words (BOW).
ii. Statistically analyze the distribution of their emotions and discover how their emotions vary based on their ethnic race.
    a. Plan: Using Friedman's test and Bonferroni adjustment.

3.2 Data Understanding

This phase focusses on data collection and activities to get familiarized with it, and to identify data quality problems. Benchmark data was used for this study, so no data collection was done. The dataset used was obtained from the Texas Department of Criminal Justice website. It contains the last statements made by executed death row inmates from 1982 to 2017, with a total number of executions of 544 out of which 200 are aged 35 years and less at the time of writing this report.

3.3 Data Preparation

The data preparation phase covers all activities to construct the final dataset (data that will be fed into the modeling tool(s)) from the initial raw data. Before the analysis, 126 out of the 200 inmates aged 35 and below last statements made in English language were collected. 25 out of the 126 inmates declined to make statements, so 101 statements were prepared for the emotion detection and analysis. A cleaned text file was created by removing special characters and paragraph breaks.

3.4 Modelling

Modeling techniques are selected and applied, and their parameters are calibrated to optimal values. Naïve Bayes is the algorithm for modelling and training the classifier. It is a classifier named after Thomas Bayes (1702 – 1761) is a learning algorithm as well as a statistical method for classification. It captures uncertainty in a principled way by using probabilistic approach. Naive Bayesian classification provides practical learning algorithms and prior knowledge and observed data can be combined. The training set that consists of the following language models:

i. Unigram: 515 instances
ii. Bigram:3 instances

The training dataset contain six classes, which are: sadness, joy, fear, surprise, love, and anger. The experiments for this study were implemented in Python using TextBlob. It is a Python version 2 and 3 library for processing textual data. It provides a simple API for diving into common natural language processing (NLP) tasks such as part-of-speech tagging, noun phrase extraction, sentiment analysis, classification, and translation.

3.4.1 Emotion Classification.

The emotion classification is in two levels. The levels are:

i. Statement level: This is the emotion score for the complete statement given by the executed inmate.
ii. Sentence level: This is the emotion score for individual sentences contained within the statement given by the executed inmate.

For the sentence level classification, the probability distribution across the six emotion classes is indicated and the class with the highest value is set as the statement level emotion class.

3.5 Data Analysis

The statistical analysis is in SPSS using Friedman's test. The test is used to test for differences between groups when the dependent variable being measured is ordinal or continuous. The default significance threshold was used, which is 0.05. The analysis is in the following stages:

i. Ranking emotions within cases
ii. Computing mean rank over cases
iii. Friedman's test analysis
iv. Bonferroni adjustment

4. RESULTS AND DATA ANALYSIS

Results in this section are grouped into two:

i. Experiments Result: This shows and discusses the result obtained from the emotion classification experiments.
ii. Statistical Analysis Result: This shows and discusses results of statistical analysis conducted on classified emotions from conducted experiment.

4.1 Experiment Results

Varying emotions were detected from the executed inmates' last statements. Table 2 shows the different emotions detected per each inmate statement from 20 out of the 101 inmates with its Naïve Bayes score, and then the emotion with the highest score is set as the emotion for the statement given by the executed inmate. The complete 101 inmate's emotion score is shown in the appendix of this study. However, the different emotions from the 101 records is shown in Figure 2.

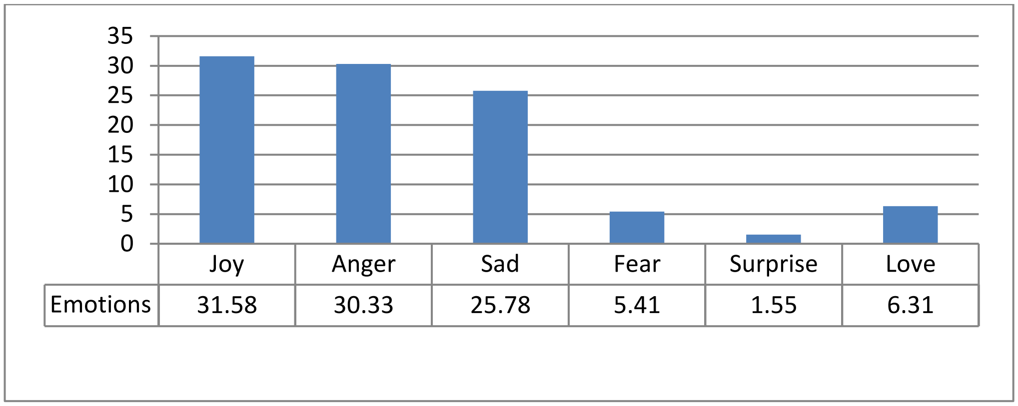

Figure 2. Executed inmate's emotion score bar chart

Table 2. Computed inmate's emotion score

Joy	Anger	Sad	Fear	Surprise	Love	Emotion	Race
0.27	0.05	0.65	0.03	0	0	Sad	Black
0	0.21	0.19	0.06	0.31	0.23	Surprise	Black
0.55	0.05	0.38	0.02	0	0	Joy	White
0.31	0.27	0.33	0.07	0	0.03	Sad	Hispanic
0.11	0.65	0.05	0.07	0	0.12	Anger	Black
0.55	0.05	0.38	0.02	0	0	Joy	Black
0.54	0.23	0.17	0.05	0	0.01	Joy	Black
0.36	0.33	0.13	0.08	0	0.1	Joy	Black
0.07	0.61	0.24	0.05	0	0.02	Anger	Hispanic
0.02	0.4	0.04	0.08	0.03	0.42	Love	White
0.55	0.05	0.38	0.02	0	0	Joy	Hispanic
0.55	0.05	0.38	0.02	0	0	Joy	Hispanic
0.31	0.27	0.33	0.07	0	0.03	Sad	Black
0.55	0.05	0.38	0.02	0	0	Joy	White
0.23	0.62	0.08	0.05	0	0.02	Anger	Black
0.55	0.05	0.38	0.02	0	0	Joy	Black
0.07	0.17	0.68	0.05	0	0.02	Sad	Hispanic
0.11	0.65	0.05	0.07	0	0.12	Anger	Black
0.04	0.24	0.32	0.4	0	0.01	Joy	Hispanic
0.13	0.25	0.5	0.08	0	0.04	Sad	White

4.2 Statistical Analysis Result

4.2.1 Descriptive Statistics

Results from statistical analysis from Table 3 shows surprise and love have the mode value of 0, and all emotions except for anger and fear having the minimum value of 0. Anger has the minimum value of 0.03 which is stronger than that of fear 0.0.1. Also, anger has the highest maximum number 0.91 followed by surprise 0.74, joy 0.73, sad 0.68, and 0.56. Despite anger having both highest minimum and maximum values compared with other emotions, it did not achieve the highest mean score. It came in second to joy, Joy has 0.31 mean score followed by Anger 0.30, Sad 0.26, Love 0.06, Fear 0.05, and Surprise 0.02.

Table 3. Emotion Score Statistics

		Joy	Anger	Sad	Fear	Surprise	Love
N	Valid	101	101	101	101	101	101
	Missing	0	0	0	0	0	0
Mean		.31	.30	.26	.05	.02	.06
Median		.28	.24	.20	.05	.00	.02
Mode		0.55	0.05	0.38	0.02	0	0
Minimum		0	0.03	0	0.01	0	0
Maximum		0.73	0.91	0.68	0.4	0.74	0.56

Table 4. Descriptive Statistics of Emotion Score

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
Joy	101	0	0.73	32	**.31**	.231
Anger	101	0.03	0.91	30	**.30**	.240
Sad	101	0	0.68	26	**.26**	.172
Fear	101	0.01	0.4	5	**.05**	.044
Surprise	101	0	0.74	2	**.02**	.081
Love	101	0	0.56	6	**.06**	.113
Valid N (listwise)	101					

From Tables 3 and 4 it can be seen that out of the total 101 classified statements emotions. The varying distribution of emotion classes are Joy 32 statements, anger 30 statements, sad 26 statements, fear 5 statements, surprise 2 statements, and love 6 statements. Figure 3 shows the race distribution of the 101 inmates used in this study.

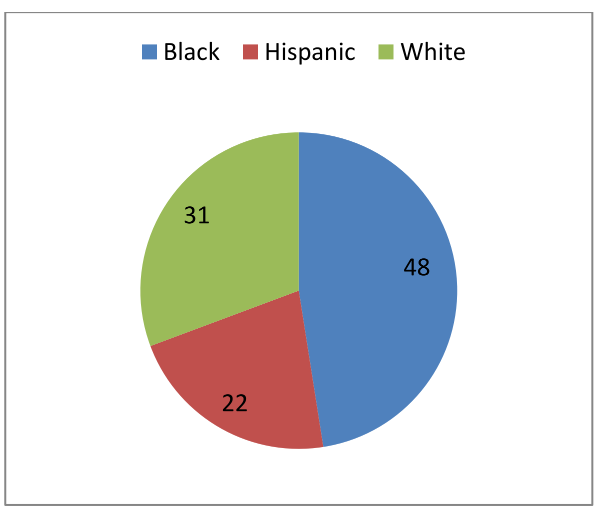

Figure 3. Race Distributions of the 101 Executed Inmates

As shown in Figure 4, the variables "Race" and "Statement Emotion" contents are in string format. To carry out the Friedman's test analysis, there is need to transform the contents from string to numeric. The transformed result is shown in Table 5.

```
GeneralEmotion into GenEmoCode
Old Value        New Value  Value Label

Anger                    1  Anger
Joy                      2  Joy
Love                     3  Love
Sad                      4  Sad
Surprise                 5  Surprise


Race into RaceCode
Old Value  New Value  Value Label

Black            1  Black
Hispanic         2  Hispanic
White            3  White
```

Figure 4. Variables Recoding

20 records from each race were selected for the Friedman's test. The selection table is shown in Table 5 and 6.

Table 5. Inmate Race Emotion Selection

White	**Hispanic**	**Black**
2	4	4
3	1	5
2	2	1
4	2	2
1	4	2
2	2	2
2	2	4
2	2	1
2	2	2
3	1	1
4	2	2
3	2	1
3	1	5
2	1	4
2	4	1
2	2	1
2	1	2

2	1	1
1	4	1
2	2	2

Table 6. Quartile Presentations of Emotion Score Based on Race Distribution

	N	Percentiles		
		25th	50th (Median)	75th
White	20	2.00	2.00	3.00
Hispanic	20	1.00	2.00	2.00
Black	20	1.00	2.00	3.50

Tables 7 and 8 show the "Chi-square", degrees of freedom ("df") and the significance level ("Asymp. Sig."). It can be seen that there is an overall statistically significant difference between the mean ranks of the related groups as shown in Tables 7 and 8.

Results of the Friedman's test in Table 8 shows there was a statistically significant difference in perceived effort depending on emotion type by executed inmate based on race, $\chi 2^{(2)} = 1.719$, $p = 0.423$.

Table 7 Mean Ranks

	Mean Rank
White	2.20
Hispanic	1.93
Black	1.88

Table 8 Friedman's Test Result

N	20
Chi-Square	1.719
df	2
Asymp. Sig.	.423

4.3 Analysis Testing

4.3.1 Friedman's Test

From the results in section 3.4.2, It can be seen that there are differences somewhere between the groups, but do not know exactly where those differences lie. Therefore the Post Hoc Test using Wilcoxon signed-test was used to examine where the differences actually occur.

Table 9. Wilcoxon Emotion Race Comparison Ranks

		N	Mean Rank	Sum of Ranks
Hispanic - White	Negative Ranks	9[a]	5.56	50.00
	Positive Ranks	4[b]	10.25	41.00
	Ties	7[c]		
	Total	20		
Black - White	Negative Ranks	9[d]	6.83	61.50
	Positive Ranks	6[e]	9.75	58.50
	Ties	5[f]		
	Total	20		
White - Hispanic	Negative Ranks	4[g]	10.25	41.00
	Positive Ranks	9[h]	5.56	50.00

	Ties	7[i]		
	Total	20		
Black - Hispanic	Negative Ranks	7[j]	5.21	36.50
	Positive Ranks	5[k]	8.30	41.50
	Ties	8[l]		
	Total	20		
White - Black	Negative Ranks	6[m]	9.75	58.50
	Positive Ranks	9[n]	6.83	61.50
	Ties	5[o]		
	Total	20		
Hispanic - Black	Negative Ranks	5[p]	8.30	41.50
	Positive Ranks	7[q]	5.21	36.50
	Ties	8[r]		
	Total	20		
a. Hispanic < White				
b. Hispanic > White				
c. Hispanic = White				
d. Black < White				
e. Black > White				
f. Black = White				
g. White < Hispanic				
h. White > Hispanic				
i. White = Hispanic				
j. Black < Hispanic				
k. Black > Hispanic				
l. Black = Hispanic				
m. White < Black				
n. White > Black				
o. White = Black				
p. Hispanic < Black				
q. Hispanic > Black				
r. Hispanic = Black				

Results from Table 9 show that on:

i. Hispanics to Whites comparison, 9 Whites executed inmates had a higher Emotion Score than Hispanics. However, 4 Hispanics had a higher Emotion Score than Whites and 7 executed Hispanics and Whites had no difference in their Emotion Score.

ii. Black to White comparison, 9 Whites executed inmates had a higher Emotion Score than Blacks. However, 6 Blacks had a higher Emotion Score than Whites and 5 executed Blacks and Whites had no difference in their Emotion Score.

iii. White to Hispanic comparison, 4 Hispanics executed inmates had a higher Emotion Score than Whites. However, 9 Whites had a higher Emotion Score than Hispanics and 7 executed Whites and Hispanics had no difference in their Emotion Score.

iv. Black to Hispanic comparison, 7 Hispanics executed inmates had a higher Emotion Score than Blacks. However, 5 Blacks had a higher Emotion Score than Hispanics and 8 executed Blacks and Hispanics had no difference in their Emotion Score.
v. White to Black comparison, 6 Blacks executed inmates had a higher Emotion Score than Whites. However, 9 Whites had a higher Emotion Score than Blacks and 5 executed Blacks and Whites had no difference in their Emotion Score.
vi. Hispanic to Black comparison, 5 Blacks executed inmates had a higher Emotion Score than Hispanics. However, 7 Hispanics had a higher Emotion Score than Blacks and 8 executed Hispanics and Blacks had no difference in their Emotion Score.

4.3.2 Bonferroni Adjustment

Bonferroni adjustment on our results from the Wilcoxon tests was made because it is making multiple comparisons. So our adjusted significance level is obtained by dividing 0.05 our current significance level by number of comparisons which is 6. Result is 0.0083, which is our new significance level.

Table 10. Wilcoxon Test Statistics

Test Statistics[a]						
	Hispanic - White	Black - White	White - Hispanic	Black - Hispanic	White - Black	Hispanic - Black
Z	-.321[b]	-.088[b]	-.321[c]	-.198[c]	-.088[c]	-.198[b]
Asymp. Sig. (2-tailed)	.748	.930	.748	.843	.930	.843
a. Wilcoxon Signed Ranks Test						
b. Based on positive ranks.						
c. Based on negative ranks.						

Table 10 shows changes between emotions score of the different races, and it leads to overall to a statistically significant difference. Comparing the “Asymp. Sig. (2-tailed)” values with our significance level $p < 0.0083$ it is discovered that there was no statistical significant difference between the races in terms of emotion classes.

5. CONCLUSION

Although anger achieved both highest scores for minimum and maximum values compared to other emotions; it did not achieve the highest mean score. It came in second to the emotion Joy; Joy has 0.31 mean score followed by Anger 0.30, Sadness 0.26, Love 0.06, Fear 0.05, and Surprise 0.02. There was a statistically significant difference in emotions depending on executed inmate race class at, $\chi 2^{(2)} = 1.719$, $p = 0.423$. Post hoc analysis with Wilcoxon signed-rank tests was conducted with a Bonferroni correction applied, resulting in a significance level set at $p < 0.0083$. Using the new significance level and checking the condition level $p < 0.0083$, there were no significant differences between the different races.

Conflict of interest

The authors declare that there is no conflict of interests with anybody or any institution regarding the publication of this paper.

References

[1] African Youth Charther. (2014). *Igarss 2014*. Charter, African Union Commission. http://doi.org/10.1007/s13398-014-0173-7.2.

[2] Al-Kharusi, M. I., Usman, A. I., and Awwalu, J. (2015). Application of Sentiment Analysis in Business Intelligence. *International Journal of Knowledge, Innovation, and Enterepreneurship*, *3*(3), 51–60.

[3] An, Y., Sun, S., and Wang, S. (2017). Naive Bayes classifiers for music emotion classification based on lyrics. In *2017 IEEE/ACIS 16th International Conference on Computer and Information Science (ICIS)* (pp. 635–638). IEEE. http://doi.org/10.1109/ICIS.2017.7960070.

[4] Avetisyan, H., Bruna, O., and Holub, J. (2016). Overview of existing algorithms for emotion classification. Uncertainties in evaluations of accuracies. *Journal of Physics: Conference Series*, *772*, 12039. http://doi.org/10.1088/1742-6596/772/1/012039.

[5] Awwalu, J., Bakar, A. A., and Yaakub, M. R. (2015). Detection and polarization of political sentiments on twitter. *International Journal of Applied Engineering Research*, *10*(21).

[6] Binali, H., Wu, C., and Potdar, V. (2010). Computational approaches for emotion detection in text. In *4th IEEE International Conference on Digital Ecosystems and Technologies* (pp. 172–177). IEEE. http://doi.org/10.1109/DEST.2010.5610650.

[7] Boccaccini, M. T., and Brodsky, S. L. (2002). Death row inmate characteristics, adjustment, and confinement: A critical review of the literature. *Behavioral Sciences and the Law*, *20*(1–2), 191–210. http://doi.org/10.1002/bsl.473.

[8] Calefato, F., Lanubile, F., and Novielli, N. (2017). EmoTxt: A Toolkit for Emotion Recognition from Text. In *7th Affective Computing and Intelligent Interaction* (Vol. 1, pp. 3–4). San Antonio, Texas. Retrieved from http://arxiv.org/abs/1708.03892.

[9] Chapman, P., Kerber, R., Clinton, J., Khabaza, T., Reinartz, T., and Wirth, R. (1999). The CRISP-DM process model. *The CRIsP–DM Consortium*, *310*(C), 91. Retrieved from http://www.crisp-dm.org/Process/index.htm.

[10] Chen, M., Zhang, L., and Allebach, J. P. (2015). Learning deep features for image emotion classification. In *2015 IEEE International Conference on Image Processing (ICIP)* (pp. 4491–4495). IEEE. http://doi.org/10.1109/ICIP.2015.7351656.

[11] Durahim, A. O., Coskun Setirek, A., Başarır Özel, B., and Kebapçı, H. (2010). Music Emotion Classification for Turkish Songs Using Lyrics. *Pamukkale Univ Muh Bilim Derg*, *10*(10), 10. article. http://doi.org/10.5505/pajes.2017.15493.

[12] Hirschmüller, S., and Egloff, B. (2016). Positive emotional language in the final words spoken directly before execution. *Frontiers in Psychology*, *6*(JAN), 1–10. http://doi.org/10.3389/fpsyg.2015.01985

[13] Jang, E.-H., Park, B.-J., Kim, S.-H., Chung, M.-A., Park, M.-S., and Sohn, J.-H. (2014). Emotion classification based on bio-signals emotion recognition using machine learning algorithms. In *2014 International Conference on Information Science, Electronics and Electrical Engineering* (pp. 1373–1376). IEEE. http://doi.org/10.1109/InfoSEEE.2014.6946144

[14] Joshi, D., Datta, R., Fedorovskaya, E., Luong, Q.-T., Wang, J., Li, J., and Luo, J. (2011). Aesthetics and Emotions in Images. *IEEE Signal Processing Magazine*, *28*(5), 94–115. http://doi.org/10.1109/MSP.2011.941851

[15] Jurek, A., Bi, Y., and Mulvenna, M. (2014). Twitter Sentiment Analysis for Security-Related Information Gathering. In *2014 IEEE Joint Intelligence and Security Informatics Conference* (pp. 48–55). IEEE. http://doi.org/10.1109/JISIC.2014.17

[16] Kim, J., and André, E. (2006). Emotion Recognition Using Physiological and Speech Signal in Short-Term Observation (pp. 53–64). Springer, Berlin, Heidelberg. http://doi.org/10.1007/11768029_6

[17] Kwon, O., Chan, K., Hao, J., and Lee, T. (2003). Emotion Recognition by Speech Signals. *Conference: 8th European Conference on Speech Communication and Technology, EUROSPEECH 2003 - INTERSPEECH 2003, Geneva, Switzerland*, 125–128. Retrieved from https://pdfs.semanticscholar.org/9329/ca4c37ef89c521234debe819056baf1a7e28.pdf

[18] Marbán, Ó., Mariscal, G., and Segovia, J. (2009). *A Data Mining and Knowledge Discovery Process Model*. *Data Mining and Knowledge Discovery in Real Life Applications*. http://doi.org/10.5772/6438

[19] Medhat, W., Hassan, A., and Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. http://doi.org/10.1016/J.ASEJ.2014.04.011

[20] Spasić, I., Burnap, P., Greenwood, M., and Arribas-Ayllon, M. (2012). A naïve bayes approach to classifying topics in suicide notes. *Biomedical Informatics Insights*, *5*(Suppl. 1), 87–97. http://doi.org/10.4137/BII.S8945

[21] UNDESA. (2014). Definition of youth. *Youth - Definition* | *United Nations Educational, Scientific and Cultural Organization*. Fact Sheet, United Nations Department of Economic and Social Affairs (UNDESA. http://doi.org/10.3102/00346543067001043

[22] Wirth, R. (2000). CRISP-DM: Towards a Standard Process Model for Data Mining. *Proceedings of the 4th International Conference on the Practical Application of Knowledge Discovery and Data Mining (PADD '00)*. http://doi.org/10.1.1.198.5133