An Exploratory Data Analysis for Synchronous Online Learning Based on AFEA Digital Images

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Abstract—**The spread of COVID-19 throughout the world has affected the education sector. In some higher education institution, such as Polytechnic Caltex Riau (PCR), it is mandatory for students to participate in synchronous or asynchronous learning activities via virtual classroom. Synchronous online learning is usually supported by video conferencing media such as Google Meeting or Zoom Meeting. The communication between lecturers and students is captured as an image as evidence of students' interaction and participation in certain learning subjects. These images can provide information for lecturers in determining students' internal feelings and measuring students' interest through facial emotions. Taking this reason into account, the current research aims to analyze the emotions detected in facial expression through images using automatic facial expression analysis (AFEA) and exploratory data analysis (EDA), then visualize the data to determine the possible solution to improve the educational process' sustainability. The AFEA steps applied were face acquisition to detect facial parts in an image, facial data extraction and representation to process feature extraction on the face, and facial expression recognition to classify faces into emotional expressions. Thus, this paper presents the results obtained from applying machine learning algorithms to classify facial expressions into happy and unhappy emotions with mean values of 5.58 and 2.70, respectively. The data were taken from the second semester of 2020/2021 academic year with 1,206 images. The result highlighted the fact that students showed the facial emotion based on the lecture types, hours, departments, and classes. It indicates that there are, in fact, several factors contributing to the variances of students' facial emotions classified in synchronous online learning.**

Keywords—**Digital Images, Face Emotion, Synchronous Online Learning, Facial Expression Recognition.**

I. INTRODUCTION

COVID-19 pandemic has affected many sectors, including the education sector, so that currently conventional learning has transformed into online learning. The face-to-face learning process at the classroom is shifted to a live learning in the virtual class using synchronous or asynchronous online learning methods to support learning outcomes. Synchronous online learning is commonly supported by media such as video conferencing, instant messaging and chat; and complemented with face-to-face meetings [1]. The media used in synchronous online learning include Google Meeting, Zoom, Cisco WebEx, Skype, etc. It makes it possible for educators to analyze and monitor students' reaction, emotion, and motivation when communicating synchronously [2], [3]. There are relationships between students' motivation, participation, and performance in the online lecture [4]-[6], this is significantly correlated with grades on the exam.

Students' motivation, which can be measured by facial expression recognition, is critical to the learning process [7], [8]. Even though emotions are influenced by subjective factors, a large number of participants can ensure the level of concentration and students' expression that represent emotions. This situation disturbs educators in measuring students' interest and keeping students motivated through specific learning topics at certain times during synchronous learning. With the development of biometric technology like artificial intelligence, machine learning, and deep learning, numerous facial expression systems have been proposed to monitor students' engagement [9]-[11].

In Polytechnic Caltex Riau (PCR), one of the online educational activities is the lecturer providing lecture content via video conferencing to give lectures and to communicate with students [12]. A virtual classroom enables synchronous live face-to-face communication. In the virtual classroom, the lecturer captures the students' interaction and participation into an image. The benefit of face-to-face communication can provide information about a students' mood and emotion where faces convey multiple information that can be used to determine one's internal feeling. In this research, the online learning based on facial expressions on digital images was analyzed. The lecturers can identify and measure the student motivation, engagement, and interest to specific lecture content at certain times through facial expression.

A. *Student Learning Interest and Motivation*

Learning is a process of changing individual behavior through interaction with the environment. Learning is an active activity; it means students will be unable to change their behavior unless they actively participate in every process that takes place [5], [6]. Students' self-confidence can encourage the interest growth in learning. Parents and teachers need to improve children's self-confidence since it will foster their interest [13]. Interest in learning is an inner urge that develops from a student to raise motivation and communications characterized by a feeling of pleasure or good emotion in receiving the lessons given [6].

The definition of emotion is formulated in various ways by psychologists in different theoretical orientations. Emotion is defined as a biological and psychological state and a series of tendencies to act. Emotions simply can be defined as feelings

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or affective responses as a result of psychological vibrations, thoughts, beliefs, subjective judgements, and body expression of a stimulus; emotion as a feeling, an effect occurred when a person is in condition or an interaction that is essential [13], [14]. Emotions can either be positive or negative. Positive emotions produce pleasant feelings. In face-to-face learning in the classroom, teachers easily identify students' emotions by observing the changed emotion and behavior. A students' emotional involvement represents the level of engagement in learning which is referred to as affective engagement [13]-[15].

B. Facial Expression Recognition Technology

Facial expressions become signals for human beings to express their emotional states [16], [17]. In the current research on facial expression recognition, many researchers has introduced models that deal with expression information in facial recognition using computer vision [9], [11], [18]. This technology is able to automatically detect facial expressions in different settings, where people are studied in their natural social environment [19]. Facial expression recognition (FER) extracts and analyzes information through image or video. One of the categories of tasks in facial expression recognition is static images which are represented by photographs [7].

Generally, FER processes have three important steps: face detection, feature extraction, and classification [20]. Face detection locates faces in an image or video; feature extraction extracts information about facial features from detected faces; facial expression and emotion classification analyze and classify facial features into expression/emotion categories such as smile, frown, happiness, or anger. Face detection can create a bounding box that delimit detected faces based on regions of interest (ROIs). Most researchers detected only frontal and near-frontal views of faces [21]-[24], because it elicited higher intensity ratings [25]. When the faces are detected, the FER will process the retrieved ROIs to prepare the data that will be proceeded into the classifier. In online learning, computer vision-based biometric technology is an appropriate application for recognizing emotion as an effective way to assess student engagement [26]-[28]. In this research, we apply automatic facial expression analysis to classify emotion based on digital images.

II. MATERIAL AND METHOD

A. Data Collection and Data Preprocessing

In this research, the exploratory data analysis (EDA) method was applied. This method investigated the data to find out the patterns and found data anomalies using statistical and graphical representation of facial expressions in PCR. The data were collected from the second semester of the 2020/2021 academic year at PCR. The data were analyzed from four different study programs in the Information Technology Department, such as Informatics Engineering (IT), Information System (IS), Computer Engineering (Comp), and Magister Program (Master). The data were subclass, lecture_code, lecture_name, lecture_type, lecturer_name, lecture_date, lecture_hour, and lecture_file_captured. Subclass was the name of the classes; lecture_code was the lecture code of lecture; lecture_name was the name of the lecture being taught; lecture_type was the type of lecture such as theory class and practical class; lecturer_name was the name of the lecturer; lecture_date was the date of lecture; lecture_time was the time of lecture; lecture_file_captured was image captured in the lecture as the evidence of activity carried out by lecturers in synchronous lectures in PCR. Fig. 1 shows the dataset for this research.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1206 entries, 0 to 1205
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   subclass             1206 non-null   object
 1   lecture_code         1206 non-null   object
 2   lecture_name         1206 non-null   object
 3   lecture_type         1206 non-null   object
 4   lecture_name.1       1206 non-null   object
 5   lecture_date         1206 non-null   datetime64[ns]
 6   lecture_hour         1206 non-null   object
 7   lecture_file_capture 1206 non-null   object
dtypes: datetime64[ns](1), object(7)
memory usage: 75.5+ KB
```

Fig. 1 Information of dataset.

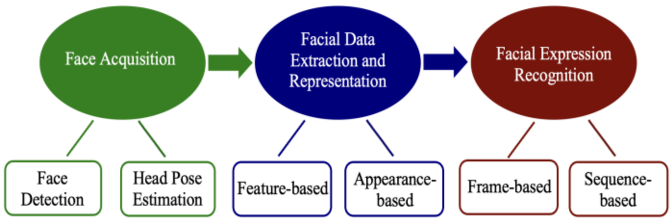

Fig. 2 Automatic facial expression analysis (AFEA) by [20].

The dataset consists of 1,206 images captured by lectures. The data were preprocessed using the Python programming language. Image data preprocessing was a sequence of processes to produce a dataset that was ready for the face recognition and expression classification steps. It converted image data into a form that can be processed by machine learning algorithms. Preprocess stages included image cropping, image resizing, image grayscale, and image normalization. Image cropping trimmed certain parts of the face in each image; image resizing resized image from varying sizes to standard size; image grayscale converted color image into grayscale image; and image normalization re-scaled image to projecting image data pixels (intensity) into predefined range.

B. Face Recognition and Expression Classification

In the face recognition and expression classification step, the automatic facial expression analysis (AFEA) was used. It consisted of three steps: face acquisition, facial data extraction and representation, and facial expression recognition. The AFEA is shown on Fig. 2.

Face Acquisition performed the process of finding facial parts automatically in the inputted image data. It detected the faces from the image and estimated the head pose. In this paper, the OpenCV library and the Haar Cascade Classifier were applied to detect faces [29]. Facial expressions were recognized from frontal view or near frontal view.

Following the detection of the face, the next step was the extraction and representation of facial data, which performed the facial feature extraction process required in the expression

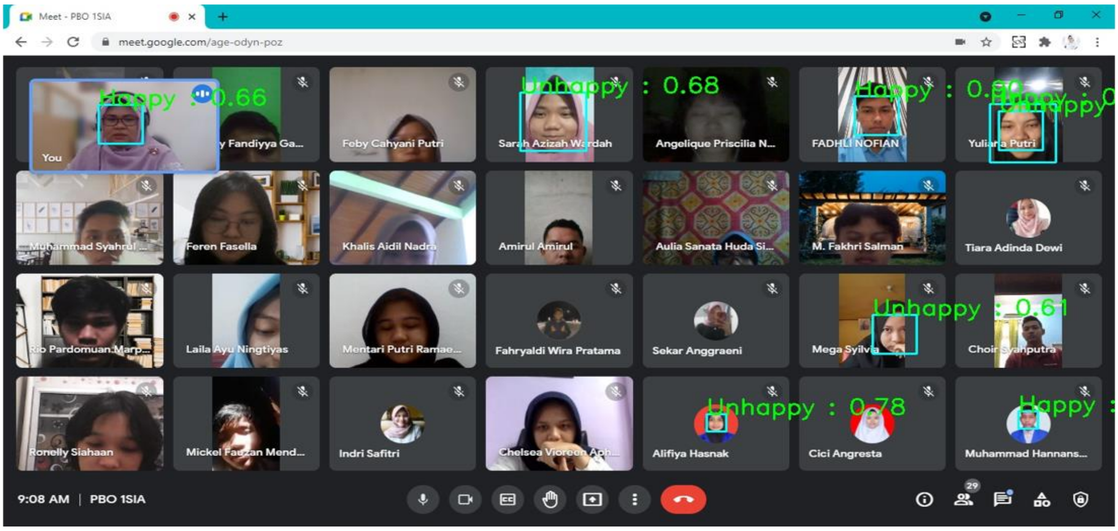

Fig. 3 Results of face expression recognition.

recognition stage. Two types of approaches in facial extraction were geometric and appearance-based methods. The geometric facial features presented the shape of facial components including mouth, eyes, brows, and nose. The appearance method filtered images to specific regions in a face image to extract feature vectors. This paper employed the principal component analysis (PCA) algorithm for facial expression analysis.

In the final stage, the facial expression recognition process was carried out to classify frame-based image approaches into two basic emotions, namely happy and unhappy, by applying the support vector machine (SVM) classifier algorithm. The input image was a static image that was classified independently. Fig. 3 shows the result of face expressions analysis from images.

C. Data Analysis and Data Visualization

In this research, 1,206 images data were classified into happy and unhappy emotion of facial expressions to measure students' interest and motivation as well as measure student engagement in synchronous online learning. The data based on type of lecture, hour of lecture, department of lecture and class of lecture were analyzed. The result resumes in the descriptive statistics can be seen on Fig. 4. It shows the value of mean, deviation standard, minimum and maximum, and quartile 1 to 3.

The overall analysis of the result (Fig. 4) indicates that the highest number of facial expressions is happy emotion, while the lowest expression is unhappy emotion with each mean value is 5.58 for happy emotion and 2.70 for unhappy. In each input image, happy emotions had a standard deviation of 3.59 and unhappy emotions had a standard deviation of 2.73, with the highest number of happy was 21 faces and unhappy was 18 faces. The distributions of each happy or unhappy class are shown on histogram on Fig. 5 and Fig. 6.

Based on the histogram on Fig. 5 and Fig. 6, the data distribution of happy emotion and unhappy emotion are skewed to the right. It suggests that most of the data values are on the left side and the tail is skewed to right when the mean value is larger than the median of the dataset. This histogram also indicates that the frequency of the happiest emotions appears more than ten times in the range of 3 or 4 faces. On the other hand, the most unhappy emotions appear more than 35 times in the range of 1 or 2 faces.

	happy	unhappy
count	1206.000000	1206.000000
mean	5.588723	2.705638
std	3.590676	2.733912
min	0.000000	0.000000
25%	3.000000	1.000000
50%	5.000000	2.000000
75%	8.000000	4.000000
max	21.000000	18.000000

Fig. 4 Descriptive statistic of image data.

For each classification result, the facial expression was visualized using boxplot and analyzed based on the type of lecture, hour of lecture, department of lecture, and class of lecture, so that the students' emotions can be revealed through facial expressions. Fig. 7 and Fig. 8 show the data visualization of happy and unhappy emotions for the types of theoretical and practical lecture; Fig. 9 and Fig. 10 show the data visualization of happy and unhappy emotions for the hour of lectures; Fig. 11 and Fig. 12 show the data visualization of happy and unhappy emotions for department of lecture; and last Fig. 13 and Fig. 14 shows the data visualization of happy and unhappy emotions for class of lecture.

III. Result and Discussion

A. Emotion Classification Based on Types of Lectures

There are two types of lectures, namely practical and theoretical lectures. Fig. 7 and Fig. 8 show the classification

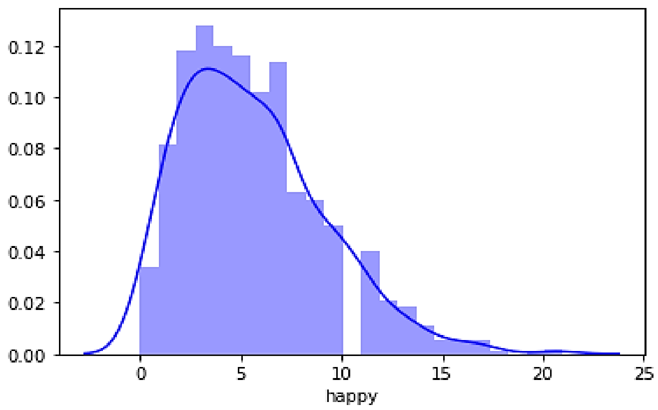

Fig. 5 Histogram of happy emotion.

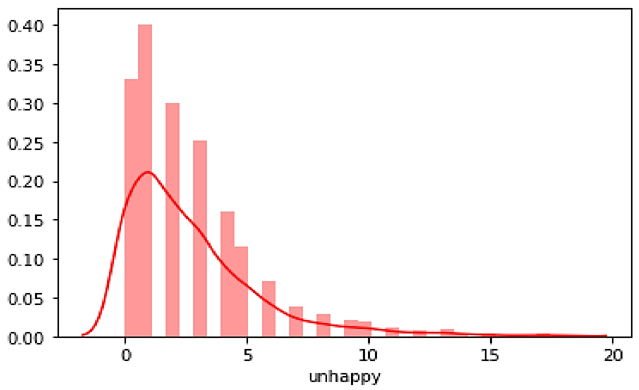

Fig. 6 Histogram of unhappy emotion.

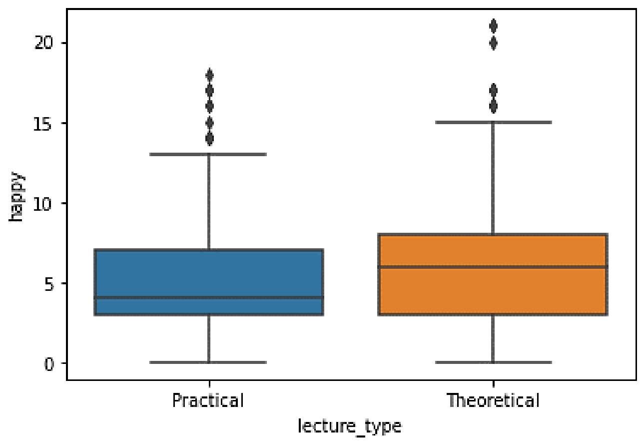

Fig. 7 Data visualization of happy emotion for types of lectures.

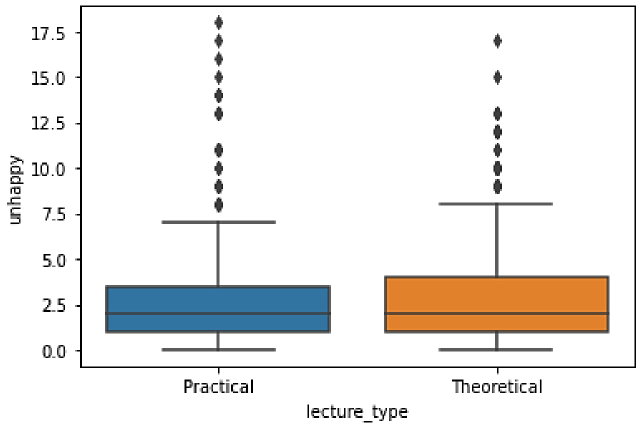

Fig. 8 Data visualization of unhappy emotion for types of lectures.

result. Fig. 7 shows that the median value for happy emotion classification based on the type of lecture is at intervals of 4-6, with the highest median value being theoretical lecture. Meanwhile, the lowest median value is practical. From the data distribution, outliers are found in the happy emotions due to the high score that is above the normal diversity in the lecture types. The outlier value for the practical type is close to 20, while the theoretical lecture type is greater than 20. The data variation for happy emotions appears to be very high in the theoretical lecture type. It can be seen in the picture of the box which is wide with a maximum number above 15.

Fig. 8 shows that the median value for the classification of unhappy emotions based on the type of lecture is at intervals of 1-2, with the highest median values being practical and theoretical lectures. As for the data distribution, some types of lectures have unhappy emotions that are considered as outliers. The outlier value for the practical lecture type is greater than 17.5, while theoretical lecture is less than 17.5. The data variation for unhappy emotions appears to be very high on theoretical lecture. It can be seen in the picture of the wide box with a maximum number approaching 10.

B. *Emotion Classification Based on Hour of Lecture*

Fig. 9 and Fig. 10 show the data distribution of facial expression based on hour of lectures. For this research, the hour of lectures was categorized into four categories, namely morning session (lectures were started at 7 a.m., 7.30 a.m., 8 a.m., 9 a.m., and 9.30 a.m.), noon session (lectures were started at 10 a.m., 10.30 a.m., and 11 a.m.), afternoon session (lectures were started at 1 p.m., 1.30 p.m., 2 p.m., 2.30 p.m., 3 p.m., 4 p.m., and 4.30 p.m.) and night session (lectures were started at 8 p.m. and 9 p.m.). After exploring the data distribution of lecture hour for the emotion classification using a boxplot, the result showed that the shape of the data distribution was very diverse and not symmetrical.

Fig. 9 shows that the median value for happy emotion classification based on lecture hour is at intervals of 4-5, with the highest median values being in the morning and afternoon sessions. Meanwhile, the lowest median value is in the noon session. From the data distribution, lecture hour with happy emotions is considered as outliers. The outlier values in the morning and afternoon sessions are both 20, while they are close to 20 in the noon session. Data variation for happy emotions are very high in the morning session. It can be seen in the picture of the wide box with a maximum number = 15.

Fig. 10 shows that the median value for unhappy emotion classification based on lecture hours is at intervals of 1-2, with the highest median values being in the morning, afternoon, and noon sessions. Meanwhile, the lowest median value is in the night session. From the data distribution, some lecture hours have unhappy emotions that are outliers. The outlier values in are close to 15 in the morning session, above 17.5 in the afternoon session, above 10 in the noon session, and close to 10

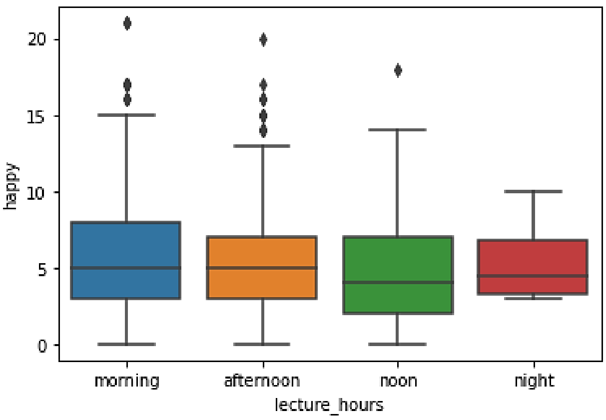

Fig. 9 Data visualization of happy emotion for lecture hour.

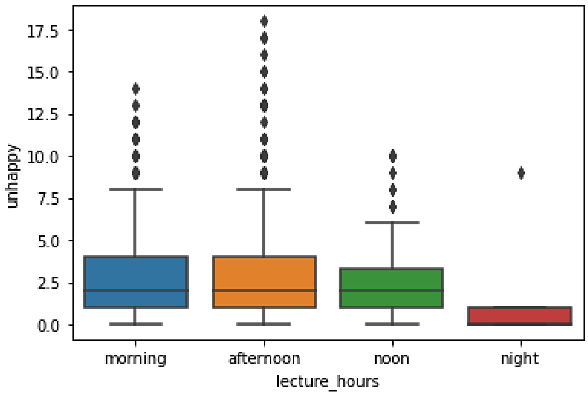

Fig. 10 Data visualization of unhappy emotion for lecture hour.

in the night session. Data variations for unhappy emotions are very high in the morning and afternoon sessions. It can be seen in the picture of the wide box with a maximum number above 7.5.

C. Emotion Classification Based on Department of Lecture

Fig. 11 shows that the median value for happy emotion classifications by department is in the interval of 4-7, with the highest median value being in the Comp department. Meanwhile, the lowest median value is in the Master department. From the data distribution, departments with happy emotions are considered as outliers. The outlier values for IT are greater than 20, while IS is close to 20. The data variation for happy emotions appears to be very high in the Comp department. It can be seen in the picture of the wide box with the maximum number approaching 20.

Fig. 12 shows that the median value for unhappy emotion classifications by department is in the interval of 1-5, with the highest median value being in the Comp department. Meanwhile, the lowest median value is in the Master department. From the data distribution, departments with unhappy emotions are considered as outliers. The outlier values for IT is close to 17.5, Master is close to 10, IS is 10, and Comp which is greater than 17.5. The data variation for unhappy emotions appears to be very high in the Comp department. It can be seen in the picture of the wide box with the maximum number approaching 15.

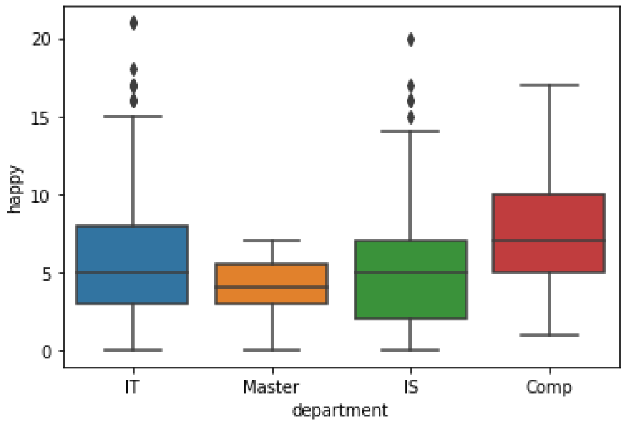

Fig. 11 Data visualization of happy emotion for department.

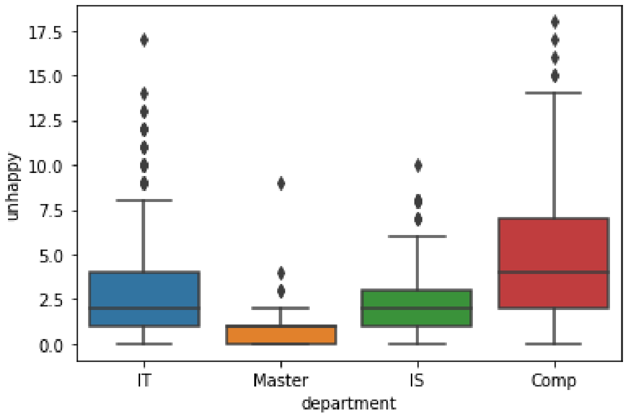

Fig. 12 Data visualization of unhappy emotion for department.

D. Emotion Classification Based on Classes of Lecture

Fig. 13 shows that the median value for happy emotion classification based on class of lecture is in the interval of 5-10, with the highest median value being in class_3. Meanwhile, the lowest median value is in class_1 and class_2. In term of data distribution, classes of lectures with happy emotions are considered as outliers. The outlier values are class_1 = 15, class_2 is above 20, and class_3 = 20. The data variation for happy emotions appears to be very high in class_2. It can be seen in the picture of the box which is wide with a maximum number above 15.

Fig. 14 shows that the median value for the unhappy emotion classification based on class of lecture is in the interval of 2-2.5, with the highest median values being in class_1 and class_2. At the same time, the lowest median value is in class_3. As for the data distribution, classes of lecture have outliers. The outlier values are close to 17.5 for class_1, above 17.5 for class_2, and above 7.5 for class_3. Data variation for unhappy emotions is very high in class_1 and class_2. It can be seen in the picture of the wide box with the maximum number above 7.5.

IV. CONCLUSION

This research was started from collecting the dataset of images captured by lecturers during synchronous online learning classes, which is mandatory at the Polytechnic Caltex Riau as the face-to-face communication in the classroom. The

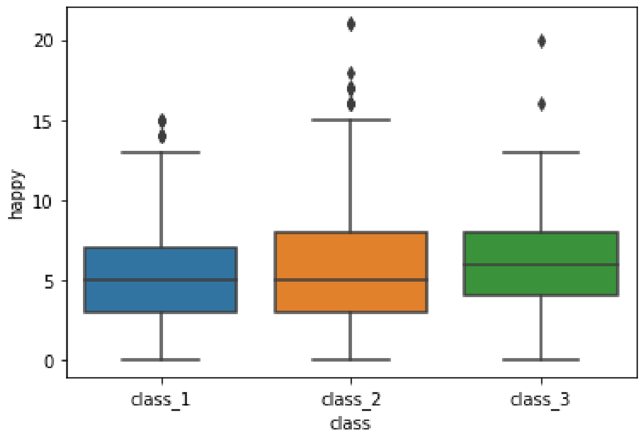

Fig. 13 Data visualization of happy emotion for each class of lecture.

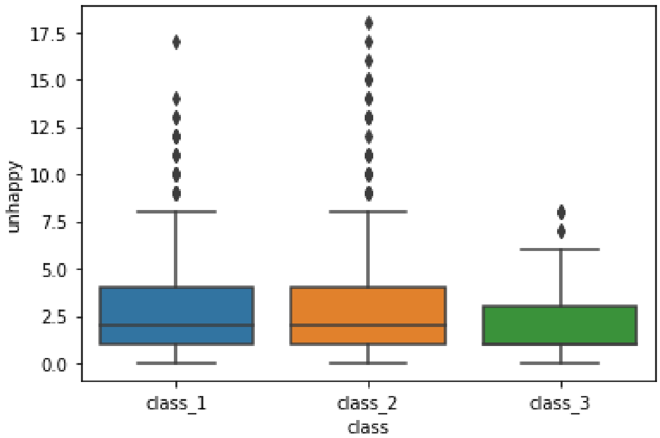

Fig. 14 Data visualization of unhappy emotion for each class of lecture.

images were classified into emotion expressions in measuring students' interest and motivation as well as monitoring students' engagement in the online learning process.

The results of the emotion classification were analyzed based on the type of lecture, lecture hour, department, and class of lecture. For the lecture type, the theoretical had the highest result on happy emotions and so did on unhappy emotions. It was shown from the maximum value, mean value, and the size of the box plotting. The results suggest that theoretical lectures have a higher influence on students' emotions than practical lectures. The results of other studies in emotion classification based on lecture hour generated different results for happy and unhappy emotions. For happy emotions, the highest data were obtained in the morning session, followed by noon session and afternoon session. Meanwhile, the lowest data was in the night session. As for the unhappy emotions, the highest value was found in the morning session and afternoon session, then followed by the noon session. Meanwhile, the lowest was night session. Based on the results of the lecture hour classification, it can be concluded that each lecture hour session affects students' emotions equally, with a mean value that is nearly identical for each classification result. Furthermore, the results of the classification of emotions based on the college department showed that the Comp department got the highest score for the happy and unhappy emotions, followed by IT and IS, while the lowest being Master department. Overall, it can be concluded that there are significant differences in the results of emotion classifications in each department. Lastly, the results of the emotion classification based on the class of students showed that in happy emotions, the highest value was students in the class 2, then followed by class 1 and class 3 which had the same value. As for unhappy emotions, the highest classification results were students in class 1 and 2, while the lowest value was in class 3. Overall, from the results of the emotion classification based on students' class, it can be concluded that students' emotions had almost equal values since they generated mean values that were almost the same.

In this study, the classification result (happy and unhappy emotions) based on the type of lectures, hour of lecture, department of lecture, and class of lecture were analyzed and visualized. Moreover, face detection to separate face on camera or face on profile photos will be the future research.

Conflict of Interest

The author states that there is no conflict of interest, either in certain circumstances or personal interests that will affect the representation or interpretation of the research results

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