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Facial Micro Expression Recognition for Feature Point Tracking using Apex Frames on CASME II Database

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Abstract: Micro-expressions are facial expressions that occur inadvertently to hide true feelings (emotional leaks). Although previous studies used the entire face area and all frames in the video dataset, this resulted in relatively long computation time and data redundancy. The main contribution of this research is to apply recognition micro-expression analysis using a comparison of apex frames with manual (handcrafted) and random sampling of frames and applying feature point tracking to the brow area and corners of the lips. The method for forming feature points in the facial area uses Discriminative Response Map Fitting (DRMF), then facial feature points are tracked using Kanade-Lucas-Tomasi (KLT). This feature point tracking produces motion feature data as feature extraction data. Finally, a comparative analysis of the classification method using the Support Vector Machine (SVM) and MLP-Backpropagation was conducted using the CASME II dataset. The experimental results of this study show significant results with an accuracy of 81.3% on MLP-Backpropagation and an average computing time of 1.45 seconds for each video. From the results of this study, information on the apex phase can contribute information that is very important for facial micro-expression recognition.

Keywords: apex frame; KLT; micro-expressions; motion features; point feature tracking

INTRODUCTION

Micro-expression is an involuntary facial muscle movement that occurs in a short time to express emotions in high-stake situations, where the human is trying to hide true feelings (emotional leakage)(Ekman and Friesen 1971). Micro-expressions have six emotional state categories: happiness, fear, sadness, surprise, anger and disgust. Unlike Macro-expressions, physiological studies (Ekman 2009) show that micro-expression occurs in short duration and subtle of muscle movements. Micro-expression are micro (short duration) and small movement intensity (subtle), occurs between 0.04 to 0.2 seconds with areas of movement only in some parts of the face (Ben et al. 2021; Hashmi et al. 2021; Tran et al. 2020).

In communication, it is not easy to recognize the genuine emotions shown by a person. On of the micro-expression implementations performs expression analysis to detect fraud (Ekman 2009) and has several potential applications in fields such as police fore lie detection (Jordan et al. 2019; O'Sullivan et al. 2009). Thus, recognizing micro-expressions can help to assist the work of experts in identifying micro-expressions well. This study aims to provide information quickly and accurately in identifying hidden emotional changes by utilizing phase comparisons in expression. Micro-expressions are facial movements dynamically sequentially with the following phases: neutral-onset-apex-offset-neutral (He et al. 2021). Starting phase in neutral state, and the onset phase shows the expression condition where the muscle intensity decreases to its original position (Yao et al. 2018). Ekman an expressionist, states that "frames that have been extracted at a point when the expressions at its peak can be easily analyzed as an emotional message". In other words, the frame contributes the preliminary information for recognition of facial micro-expressions.

This study proposes a micro-expression recognition approach by comparing apex phase with neutral phase on a series of CASME II video database frames. Using strong motion information (apex phase) produces data with accurate results and reduces redundancy data in the feature extraction process. Apex frames information in this study uses phase information data attached to CASME II file. It aims to validate that proposed method can provide class information corresponding to a CASME II compliant expressions class. This study uses KLT

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feature point tracking method. Facial features components only uses certain areas is eyebrows, eyes, and corners of mouth (Asmara et al. 2019; Choirina and Rosiani 2020). Facial area is marked with points using DRMF method. Testing process using database micro-expression is CASME II, which consist of 3 expression classes: disgust, happiness, and surprise.

LITERATURE REVIEW

A previous study by Liong dkk (Liong, Gan, et al. 2018), performed feature extraction from frame onset and offset by manual and random comparison. This research aims to improve the performance of micro-expression recognition. Several combinations of frames analyzed include random&onset and apex&onset. Furthermore, the feature extraction process uses Local Binary Pattern (LBP), Histogram of Oriented Optical Flow (HOOF), and Bi-Weighted Oriented Optical Flow (Bi-WOOF) for each frame combination. The results of this study indicate that the combination of apex&onset frame with Bi-WOOF provides 61% accuracy in CASME II with SVM-LOSOCV classification. The computing time resulting from the study to process two frames shows an average duration 0f 3.9499 seconds on MATLAB with Intel Core i7-4770 CPU 3.4Ghz. this time is quite long because it processes pixels of the entire face area simultaneously.

Precise location of facial point features on facial components plays an important role in data retrieval in micro-expression recognition. For example, Yan dkk, states that two most expressive parts of the face in the eyebrows and mouth(Yan et al. 2014). Ringeval dkk (Ringeval et al. 2015), analyzed facial features by dividing landmarks into 3 groups : left eye+eyebrow, right eye + eyebrow, and mouth. The advantages of feature extraction of a part of area over the whole face are 1) reducing face area that is less relevant to the expression and 2) reducing the execution time of process because processed area will be smaller. Based on research (Ringeval et al. 2015; Yan et al. 2014) this study combines the facial components of the eyebrows, eyes and mouth areas to be identified for movement. Ringeval and Yan's uses Regions of Interest (ROIs) for all area components to make the matching area wider. In this study, only a few small parts were used with prominent point markers and were considered to represent movement of each facial muscle. Formation of each point representing a prominent facial component using one of facial landmark methods is Discriminative Response Map Fitting (DRMF).

Previous research (Choirina and Rosiani 2020) that researchers carried out to analyze movements for tracking features points in area of eyebrows, eyes and corners of mouth using Kanade-Lucas-Tomasi (KLT) method. The research tracks all predetermined points starting from the frame in neutral phase untul it returns to neutral phase. The study used 6 video sample data with a total of 1606 frames and gave 100% research results, which means that all features can be adequately tracked.

METHOD

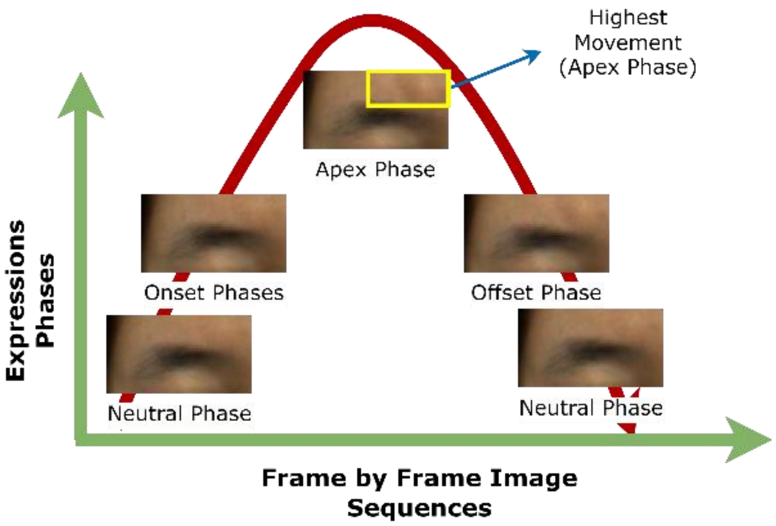

Figure 1. Micro-expression phases in CASME II (07_EP06_02_01 – disgust) (Kumar et al. 2019)

In this section, we describe in more detail framework for micro expression recognition in this study. This study contributes to recognizing micro-expressions using apex frame by tracking feature points on facial components fo eyebrows, eyes and corner of mouth area. **Error! Reference source not found.**, uses facial c omponent of left eyebrow area to show micro-expression phase's muscle movement. With human eye vision, the movement of micro-expressions in neutral to onset phase showed nothing movement in facial muscle at left eyebrow area. However, in onset to apex phase, visible movement of eyebrows indicates a reaction to the

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resulting expression. Furthermore, from apex to offset phase the movement of facial muscles on left eyebrow shift to default position until finally returns to initial position, indicating that expression phase return to neutral.

From previous explanation, it seems easy to distinguish micro-expressions phases if the frame image used for comparison is a frame that corresponds to these phases. In fact, CASME II micro-expressions database it is in the form of a video containing a series of consecutive frames, which causes subtle movements between current frame and reference frame, resulting in a lack of clarity in the information generated during feature extraction process. To overcome this problem, this study uses frames in neutral and apex phases. This analyzes the frame in neutral and apex phases to make resulting motion more precise and easier to analyze. By comparing the two frames, the muscle movements generated in each facial component can be easily identified by KLT feature point tracking method. In addition, movement analysis using two frames considered necessary can reduce redundancy data, considering that movement produced by micro-expressions has the characteristics of brief duration and subtle movement.

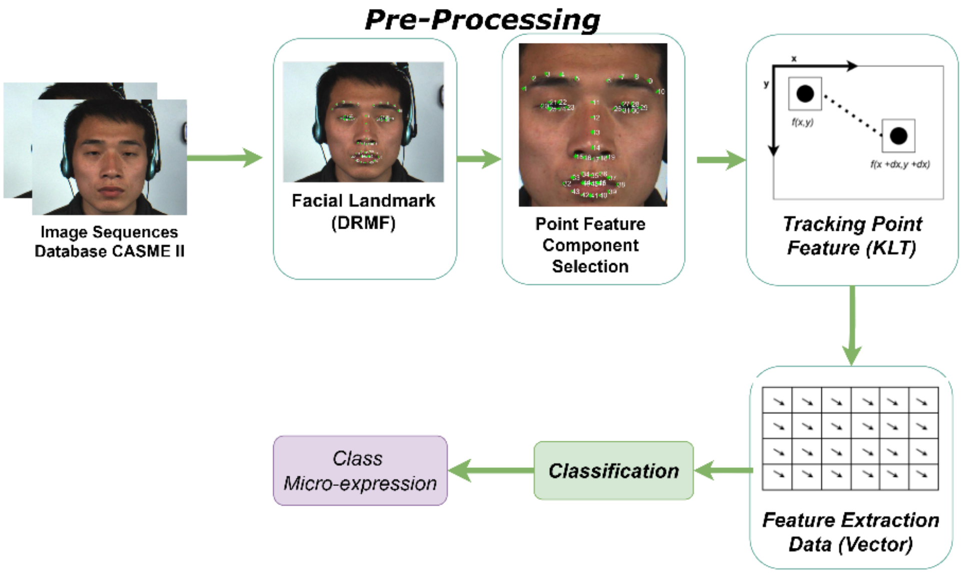

Figure 2. Facial micro-expression recognition system framework based on point feature tracking using the apex phase in the micro-expression database.
Source : researcher property

Figure 2 is design of framework proposed in this research. First step to prepare frames needed for recognize is neutral and apex frames. Phases of CASME II are already available in the information database, so this research draws on that information. Furthermore, facial detection and marking of feature point tracking is carried out by identifying between the neutral and apex frames. Identifying the displacement of detected feature points is features data in motion feature. From motion features data, which consists of 4 components, X coordinate, Y coordinate, magnitude and orientation, a classification process will be carried out to build a model for experimental data. It will be explained in the following sub-chapter for a more detailed explanation.

Pre-processing

Facial landmark detection using DRMF method, applies 49 points spread across all facial components, illustrated in Figure 4. DRMF method is a new discriminatory regression-based approach in the CLM framework. This method performs well in general facial landmark conditions and particularly suitable for dealing with dynamic background objects, large amounts of occlusion, and illumination conditions. In addition, this method has a lower computation time in real-time condition(Asthana et al. 2013). Figure 3 (a) is a pre-processing stage that includes: a) the frame image in neutral phase in CASME II video database, b) facial detection using Viola-Jones method, c) determining the point feature area required for further processing. All stages in pre-processing only use frame images from neutral phase, and then all feature point data used is a reference for tracking in the following process.

Facial detection method is a step to separate the object of face from foreground in image using viola-jones method. This method produces Region of Interest (RoI) data (Rosiani et al. 2018). After RoI is found, find each component of facial area using DRMF method. Of the 49 scattered feature points (see Figure 3 (a)), selecting the required feature areas is proper: right eyebrow, left eyebrow, right eyelid, left eyelid and corner of mouth. Determination of facial points using reference point sequence in Table 1. The component of left eyebrow area, using points 2 to 5, means that left eyebrow has 4 points that will be tracked.

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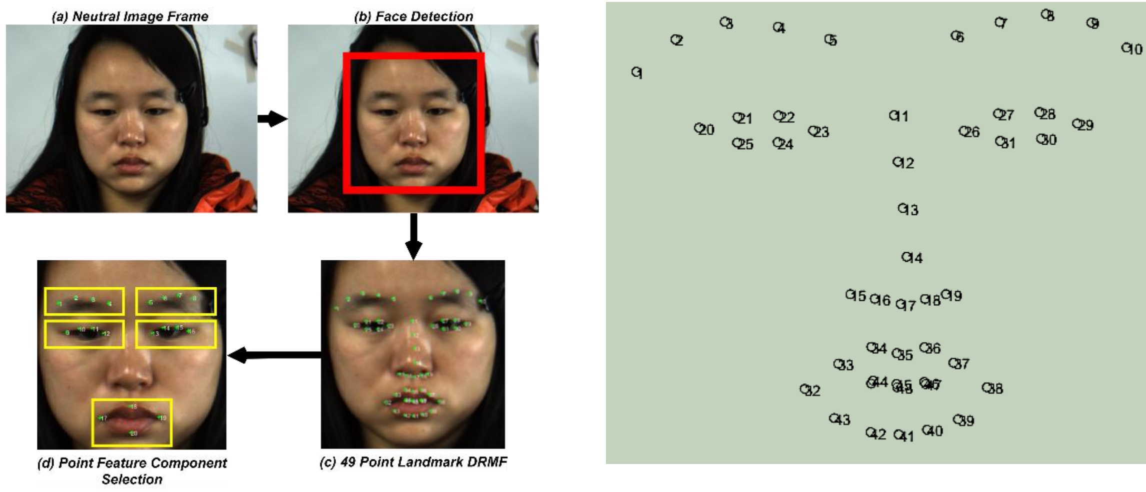

(a) (b)

Figure 3. (a) Stages of Formation of Feature Points on Facial Components, (b) The distribution of feature points on the face results is 49 points using the DRMF method.

Table 1. Facial Area Component Feature Points

No	Facial Features	Point to-	Number of Feature Points
1	Left Eyebrow	2-5	4
2	Right Eyebrow	7-10	4
3	Left Eye	20-23	4
4	Right Eye	26-29	4
5	Corner of Mouth	32,35, 38 and 41	4
		Total	**20**

One of advantages of KLT tracking method is that resulting detection can detect feature points that have good feature to track properties (Jianbo Shi and Tomasi 1994). Therefore, determining good feature points with prominent textures can be overcome by determining feature points of area components with DRMF method. Tracking points using KLT method, calculating the movement of points that are tracked from current frame and reference frame (Asmara et al. 2019; Yongyong et al. 2020), an illustration of the image can be seen in Figure 4. This method can track motion on facial area in two simple steps: a) finding the feature points that have been previously initiated in current frame, in this case, it can be interpreted as a neutral phase image frame, b) these points are tracked according to the displacement point in reference frame (frame apex).

The workflow stages KLT are 1) initiating feature points to be tracked, 2) moving feature points in reference frame, calculating the minimum error process with displacement feature, 3) features are classified into 2 parts, foreground and background features, 4) the result of total displacement of target is calculated by changing the displacement obtained for each foreground point feature, the weight depends on the distance of each point to center. Each coordinate of the change points of each frame is stored for feature extraction.

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Tracking Point Features using KLT

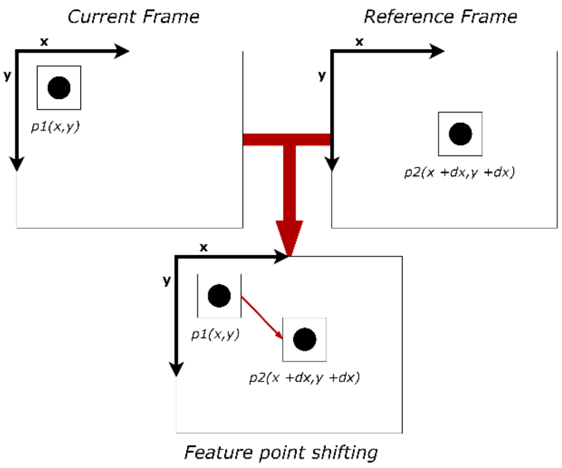

Figure 4. Illustration of point movement on current frame and reference frame

Feature Extraction

After feature point tracking stage in each frame is carried out, it will generate data from tracking feature points which are calculated as in Table 1, the next process to perform feature extraction on data (Feature Extraction). Feature extraction is the process if taking features from an object. This study used features from tracking process to extract characteristics of motion features (Lu, Kpalma, and Ronsin 2018) from changes in location of each point displacement (see Figure 5). Motion features consist of 4 components, coordinates X, coordinates Y, magnitude ($|\overrightarrow{PQ}|$), and orientation $O_{x,y}$). The motion feature components can be formulated as follows:

$$RX = (x_{p,f} - x_{p,f-1}) \quad (1)$$

$$RY = (y_{p,f} - y_{p,f-1}) \quad (2)$$

where $x_{p,f}$ dan $y_{p,f}$ point features for RX and RY in reference frame $x_{p,f-1}$ and $y_{p,f-1}$ denotes a current frame. Equation 1 and 2 produce the value of feature different (displacement) for each feature point being tracked. There are 20 feature points in each frame, resulting in a vector dimension of 20 data. The point displacement in each frame produces a vector with vector components, magnitude and orientation (theta). Equation 3 is a formula to calculate the magnitude of the two frames (current and reference frame).

$$|\overrightarrow{PQ}| = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (3)$$

where the magnitude symbol is defined $|\overrightarrow{PQ}|$. If the coordinates of the starting and ending points feature of vector are known, then the distance calculation can be used as a reference to find magnitude. The direction (orientation) of vector is the size of angle formed with the horizontal line. Equation 4 describes formula for orientation (theta).

$$O(x,y) = tan^{-1}\frac{i_{(x,y)}}{j_{(x,y)}} \quad (4)$$

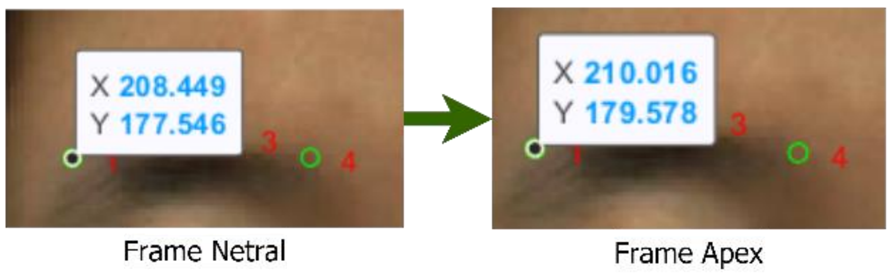

Figure 5. The coordinates of displacement of left eyebrow area between the neutral frame and the apex frame on video disgust-07_EP06_02_01

Figure 6 contains information on the coordinates of 1st feature point in the left eyebrow area, which has two parts: the neutral frame (current frame) and the apex frame (reference frame). In current frame, position of the 1st point at coordinate $(x, y) = (208,177)$. Point tracking with KLT method is done by tracking the feature points between two frames sequentially, from process shows that in left eyebrow area, there is a shift in first point.

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Currently, the first point on the apex frame is at coordinate position $(x, y) = (210, 179)$. Furthermore, two coordinates will be calculated using vector components Equation 1 to 4. The results of all feature area components in video "Disgust-07_EP06_02_01" are shown in Table 2.

Table 2. Calculation of Motion Features Extraction Data KLT Tracking Results on *Video Disgust-07_EP06_02_01*

Features	Points	Neutral Frame Coordinates		Apex Frame Coordinates		Vector Component *(Motion Features)*			
		x	y	x	y	RX	RY	$\lvert\overrightarrow{PQ}\rvert$	$\Theta(x, y)$
Left Eyebrow	*1*	*70*	*106*	*71*	*108*	*1*	*-2*	*2.24*	*297*
	2	*95*	*97*	*97*	*99*	*2*	*-2*	*2.83*	*315*
	3	*121*	*100*	*121*	*99*	*0*	*1*	*1.00*	*90*
	4	*147*	*106*	*152*	*109*	*5*	*-3*	*5.83*	*329*
Right Eyebrow	*5*	*211*	*104*	*211*	*105*	*0*	*-1*	*1.00*	*270*
	6	*233*	*97*	*233*	*99*	*0*	*-2*	*2.00*	*270*
	7	*256*	*93*	*257*	*94*	*1*	*-1*	*1.41*	*315*
	8	*279*	*97*	*279*	*98*	*0*	*-1*	*1.00*	*270*
Left Eye	*9*	*82*	*151*	*83*	*152*	*1*	*-1*	*1.41*	*315*
	10	*101*	*146*	*102*	*147*	*1*	*-1*	*1.41*	*315*
	11	*122*	*145*	*121*	*146*	*-1*	*-1*	*1.41*	*225*
	12	*139*	*152*	*139*	*153*	*0*	*-1*	*1.00*	*270*
Right Eye	*13*	*215*	*153*	*215*	*153*	*0*	*0*	*0.00*	*0*
	14	*232*	*144*	*233*	*144*	*1*	*0*	*1.00*	*0*
	15	*253*	*143*	*253*	*144*	*0*	*-1*	*1.00*	*270*
	16	*272*	*149*	*272*	*149*	*0*	*0*	*0.00*	*0*
Mouth	*17*	*135*	*284*	*135*	*284*	*0*	*0*	*0.00*	*0*
	18	*181*	*266*	*181*	*266*	*0*	*0*	*0.00*	*0*
	19	*227*	*283*	*227*	*283*	*0*	*0*	*0.00*	*0*
	20	*182*	*307*	*181*	*307*	*-1*	*0*	*1.00*	*180*

RESULT

Description of Evaluation Data

In this study, performance evaluation process using CASME II database, one of the micro-epxression databases widely used by previous studies. The object of video database was analyzed using four expression classes: disgust, sadness, surprise, and happiness. The amount of data from each class can be seen in Table 2. CASME II contains 247 micro-expression video samples obtained from 26 participants. The video was recorded using a Point Gray GRAS-03K2C camera with a high temporal resolution of up to 200 fps and resolution of 280x340 pixels. The CASME II database contains information on expression phases and action units (AUs) that can help retrieve frame images according to that information. This study used some of data from CASME II video, total 115 videos (see Table 2). The data is spread over 4 classes: disgust, happiness, sadness, and surprise. Data distribution for introducing micro-expressions at classification process is divided into 60% for training data and 40% for testing data in each class.

Table 3. CASME II Database Micro-Expression Test Data Video Sample

No	CASME II Class	Number of Data		
		***Training* (60%)**	***Testing* (40%)**	**Total**
1	Disgust	37	24	61
2	Happiness	19	12	31
3	Surprise	14	9	23
			Total	**115**

Computational Time

Recognition of micro-expressions requires real-time processing time; in terms of analysis, it requires quick processing. Experiments in this research were carried out on MATLAB software with computer specifications Intel Core i5 for CPU, with RAM 4GHz using 64-bit Windows Operating System. Table 4 shows the time comparison for overall requirements of micro-expressions recognition processing with CASME II database between previous study (Liong, See, et al. 2018). Previous research (Liong, See, et al. 2018) used the onset and apex frames with Bi-WOOF method using a large block size comparison in facial area for feature extraction

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process. As a result, the process takes an average 3,9499 seconds. This research resulted in relatively extremely fast processing time of 1,454 seconds.

Micro Expression Recognition Classification

In this study, a feature extraction process was carried out in form of motion features data from neutral and apex frames using a comparison of Support Vector Machine (SVM) and Multi-Layer Perceptron (MLP) classification methods. The method measures the resulting accuracy in classifying emotions in micro-expressions. Implemented SVM is non-linear using Radian Basis Function (RBF) kernel. Therefore, RBF kernel on system can perform sample mapping to a higher dimensional space. In comparison, MLP method used a popular training algorithm is backpropagation. In addition, algorithm used logistic sigmoid activation function. The resulting time is relatively fast due to the very small feature area that is processed so it requires fast processing time. Learning rate applies a value of 0,0001 (between 0-1) with an epoch value in training process of 200.

Table 4. Handcrafted Data Classification and Random Sampling

Classification Method	***Manual Sampling (handcrafted)* (%)**	***Random Sampling* (%)**
SVM	67,4	77,4
Backpropagation	69,6	81,3

In this classification process, the data is divided into two schemes: testing by dividing the amount of training and manually testing data with applied setting in Table 3. Second, randomly distributing training data using sampling method of Random Sampling with a percentage of training and testing data of 60% and 40%. Repeating data analysis in Random Sampling samples was performed 10 times on testing and training data. Table 5 describes two types of data processing manually and random sampling. Manual sampling with SVM method resulted in a classification accuracy of 67,4%, and with random sampling 77,4%. On the other hand, the MLP-Backpropagation method, using manual sampling, has an accuracy value of 69,6% and random sampling 81,3%. The accuracy results show that the sampling method that produces the best accuracy in this research is using random sampling on both classification methods that have been tested.

DISCUSSION

Table 5. Comparison of Micro Expression Recognition Results Using Apex Frame

Type	**Author**	**Features Extraction**	**Accuracy**
Whole Frame	(Zhang et al. 2017)	LBP-TOP and Optical Flow	*Random Forest* 62.5%
	(Zhu et al. 2018)	LBP-TOP and Optical Flow	SVM 53,3%
Frame Phase	(Asmara et al. 2019)	KLT	*Backpropagation* 61,9%
	(Liong, See, et al. 2018)	Bi-WOOF	SVM 50%
	(Liong, See, et al. 2018)	LBP	SVM 41%
	This Study	**KLT**	**SVM: 67,4%** ***Backpropagation*: 81,3%**

This section compares data extraction using whole frame and frame phases in micro-expressions. Previous research (Asmara et al. 2019; Zhang et al. 2017; Zhu et al. 2018) used whole frames on CASME II micro-expression database videos. At the same time, the study (Liong, Gan, et al. 2018; Liong, See, et al. 2018) used the onset and apex phases with two feature extraction methods is LBP and Bi-WOOF. Both were classified using the SVM method showing an accuracy of 50% for LBP and 41% for Bi-WOOF. Meanwhile, the apex frame applied information already available in CASME II in this study. The result, using KLT and motion features for features extraction process, has an accuracy of 67.4% for SVM and 81,3% for MLP-Backpropagation. Using frame types based on frame neutral and apex frame information shows the best results in analysis of Table 5 compared to using all frames in the video. In addition to high accuracy value, in terms of computational time processing, using only frames based on the expression phase is faster than using all frames on the video (see Table 4).

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CONCLUSION

In micro-expression recognition research, the apex frame is very important information because the frame can convey expression information easily. This study proposes a method of tracking feature points according to the order based on the neutral and apex phases using KLT method. The results show that the proposed method effevtively provides information based on the expression class in CASME II. The test model used two types: handcrafted data and random sampling with classification methods using SVM and MLP-Backpropagation. The best result in this study provides an accuracy of 81.3% on random sampling with MLP-Backpropagation classification method. This study's processing time is relatively fast, with an average of 1,454 seconds. For further research, it is necessary to automatically detect each expression phase in the video. This is to help analyze micro-expressions effectively and efficiently according to the apex frame information and the movement intensity extracted from the system.

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