Available *online* at : http://jitce.fti.unand.ac.id/
JITCE (Journal of Information Technology and Computer Engineering)
| ISSN (Online) 2599-1663 |

Research article

ANN Models for Shoulder Pain Detection based on Human Facial Expression Covered by Mask

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ARTICLE INFORMATION

Received: January 4th, 2023
Revised: January 31st, 2023
Available online: March 31st, 2023

KEYWORDS

Facial Expression; Pain Detection, ANN, Masked Face

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A B S T R A C T

Facial expressions are a method to communicate if someone feels pain. Moreover, coding facial movements to assess pain requires extensive training and is time-consuming for clinical practice. In addition, in Covid 19 pandemic, it was difficult to determine this expression due to the mask on the face. There for, it needs to develop a system that can detect the pain from facial expressions when a person is wearing a mask. There are 41 points used to form 19 geometrical features. It used 20.000 frames of 24 respondents from the dataset as secondary data . From these data, training, and testing were carried out using the ANN (Artificial Neural Network) method with a variation of the number of neurons in the hidden layer, i.e., 5, 10, 15, and 20 neurons. The results obtained from testing these data are the highest accuracy of 86% with the number of 20 hidden layers.

INTRODUCTION

Pain is one of the common complaints that many feel with various causes. Globally, at least 1.5 billion people have pain complaints. The results of The Global Burden of Disease 2016 study stated that high levels of pain sufferers and pain-related illnesses cause disability and a global burden of disease [1] Pain can cause various problems in individuals, such as decreased quality of life, sleep disturbances, and high rates of depression [1]. Therefore, proper treatment is needed for pain sufferers.

Facial expression is something that can be used as a parameter in pain assessment. Pain is an expression that becomes a guide when therapy occurs. Pain is an unpleasant emotional, sensory experience associated with tissue damage or tissue damage [2]. Pain assessment is beneficial for the therapist to determine the proper steps to be taken. The health worker will look at the patient's face, and based on that face, they will guess how the patient feels the pain.

Humans have the ability to read information by observing facial expressions [3]. However, this is limited due to differences in complex facial features [3]. This limitation can lead to different interpretations of pain intensity. Thus, the assessment results could be more consistent [4]. Moreover, coding facial movements to assess pain requires extensive training and is time-consuming for clinical practice [4]. In addition, the high workload of medical personnel also affects the inconsistency and inaccuracy of pain assessment results [5][6].

In 2020, there was a worldwide outbreak, namely Covid 19. Coronavirus (CoV) or coronavirus is a disease related to the respiratory tract in humans. To prevent transmission of the virus, the government has implemented a policy advising them to wear masks. In this situation, one place that must continue operating is health services such as therapy services. Therapy services must still run at the hospital. This is caused by the existence of a disease that is effectively cured by doing therapy. In order for these services to be used as they should, they are required to follow the recommendations from the government i.e wearing a mask. This raises a new problem: the need to perform a pain assessment when the patient wears a mask. Therefore, technology is needed to detect the presence or absence of pain patients feel while doing therapy, even with their faces covered by a mask.

This study aims to find a suitable ANN model to carry out binary classification of facial expressions of pain and no pain. The lower part of the face is closed, for example, when using a medical

https://doi.org/10.25077/jitce.7.01.49-55.2023

mask. Facial features are first formed to find the suitable model, which will be input into the ANN model.

METHOD

This study carried out five main steps, as shown in Figure 1. Facial features were determined first. After that, facial feature data collection was carried out from the dataset. Then the data collected is divided into training and testing data to build a model. After completion, the ANN model formed will be evaluated.

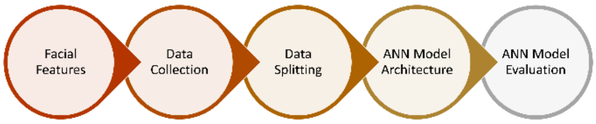

Figure 1 Methods

Facial Features

The facial features used are geometric features formed from facial points. The face point is obtained from the Dlib library. Dlib is focused on machine learning algorithms [7]. In face detection, Dlib is built based on the Histogram Oriented Gradient (HOG) and Support Vector Machine (SVM) methods [8][9]. Dlib provides a shape predictor that can be used to detect 68 facial points. Sixty-eight of these points are in the eyes' corners, the nose's tip, etc., such as. Dlib provides information on the position coordinates (x,y) of these 68 facial points based on a model trained on Dlib by applying a machine learning algorithm. mlxtend. image is part of Dlib, a library that can be used to read face landmarks [10][11]. In this library, in order to read points on faces, it is necessary to import them in the form of face landmarks. With face landmarks, point reading on the face can be made.

Because this study will capture the expression of pain when a mask covers the face, it is illustrated in the figure. At these points, it is assumed that the area around the mouth and nose is covered by a mask (figure b). Thus, facial points in that area are not used for facial feature determination. Therefore, there were 68 points from the beginning, then reduced to 41 points. The points are then used to form the geometric features of the face, as shown in Figure 2.

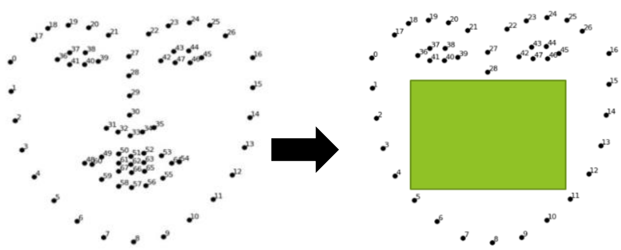

Figure 2 facial landmarks (facial points)

The facial features used in this study consist of features in the form of triangular areas and line lengths. The feature's location is divided into three parts: the lower face, the middle face, and the upper face. One of the terms used in this analysis is Horizontal thirds, which was first put forward by Leonardo da Vinci[12][13]. This term is used to divide the facial area horizontally into three parts. The division is 1/3 for the top (upper third or upper face), 1/3 for the middle (middle third or middle face), and 1/3 for the lower face (lower third or lower face) [14]. This study will use horizontal thirds to build rules for forming facial features.

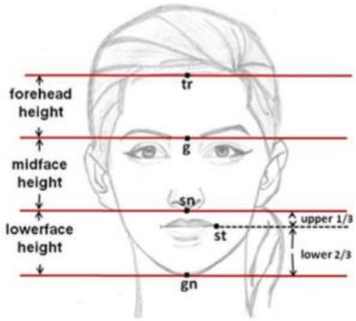

Figure 3 Horizontal thirds [12]

Lowerface

Eleven points are used to form the features on the lower face. The features are in the form of triangular features, shown in Figure 1. The facial points of the features on the lowerface are listed in Table 1.

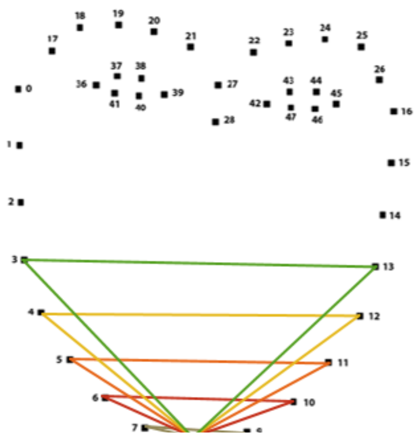

Figure 4 Facial features on the lowerface

Table 1 Facial features on the lowerface

No	Feature_ID	Facial points		
		1st	2nd	3rd
1	lowerface1	3	8	13
2	lowerface2	4	8	12
3	lowerface3	5	8	11
4	lowerface4	6	8	10
5	lowerface5	7	8	9

The value of the features is calculated using the Euclidean distance and Heron equations[15]. The first step is calculating the distance between two points using the Euclidean Distance formula, as shown in Equation (1). Where x and y are the coordinate values of a face point. After that, using Equation (2), calculate the semi-perimeter of the triangle. Where d1, d2, and d3 are the previously calculated distance values. Finally, the area of the triangle is calculated using Heron's formula in Equation (3) [57].

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$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

$$s = \frac{1}{2}(d_1 + d_2 + d_3) \tag{2}$$

$$A = \sqrt{s - (s - d_1)(s - d_2)(s - d_3)} \tag{3}$$

Middleface

On the middle face, there are 18 points consisting of 6 points each for the right eye, left eye, and the edges of the face. From that

Figure 5 Facial Features on the middleface (1)

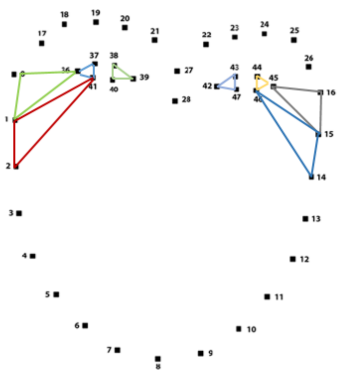

Figure 6 Facial Features on the middleface (2)

point, ten features were made, of which 2 of them are circumference values formed at points around the eye. While the other eight features are in the form of triangles which are calculated using equations (1), (2), and (3). These feature are shown on Figure 5 and 6.

The facial points of the features on the middleface are listed in Table 2.

Table 2 Facial features on the middleface

	Feature ID	Face points					
		1st	2nd	3rd	4th	5th	6th
lines	rightEye	36	37	38	39	40	41
	leftEye	42	43	44	45	46	47
triangular	rMid1	0	1	36	-	-	-
	rMid2	1	2	41	-	-	-
	rEye1	36	37	41	-	-	-
	rEye2	38	39	40	-	-	-
	lMid1	15	16	45	-	-	-
	lMid2	14	15	46	-	-	-
	lEye1	44	45	46	-	-	-
	lEye2	42	43	47	-	-	-

Upperface

On the upper face, there are 10 points consisting of five points on the left eyebrow and five points on the right eyebrow. From that point, four features can be taken, which are triangle areas and line, and there are two features in the form of triangles and two features in the form of lines.

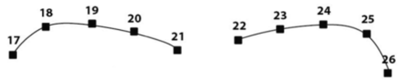

Figure 7 Facial Features on Upperface (1)

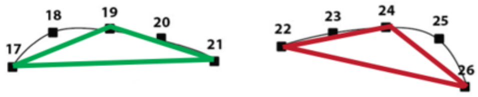

Figure 8 Facial Features on the upperface (2)

Table 3 Facial features on the upperface

feature shape	Feature ID	Face point				
		1st	2nd	3rd	4th	5th
lines	rightEyebr	17	18	19	20	21
	leftEyebr	22	23	24	25	26
triangel	rEyebrow	17	19	21	-	-
	lEyebrow	22	24	26	-	-

From this stage, 19 facial features were obtained. A total of 15 features are triangles, while the other four are lines.

Data collection

The data collection process is intended to collect values of all facial features in each frame. This study uses secondary data, namely the UNBC-McMaster shoulder pain expression archive database. This dataset contains participants who have complaints of shoulder pain. This study used a total of 20,000 frames of 24 respondents. At the frame level, this dataset provides an assessment in the form of PSPI, which evaluates based on a 0-16 pain scale. Because this study is used to detect pain (binary classification), frames with a PSPI value of 0 are declared painless. While PSPI > 0, expressed as pain. The data consisted of data containing pain and no pain. The presence of pain is coded with a value of one, while those without pain are coded with a value of zero.

Data splitting

The dataset is divided into two groups, i.e. training set and testing set. The training is used to train the ANN model. While test set is used to evaluate the model on data that has never been recognized by the model before. The number of both data are shown in Table 4.

Table 4 Data splitting

	Pain (1)	No Pain (0)	Total
Training set (70%)	4857	9143	14000
Test set (30%)	2079	3921	6000
Total			20000

ANN Models training

ANN consist of three layers i.e input layer, hidden layer and output layer. The number of neurons in the input layer depends on the number of input variables. At the output layer, the number of neurons correlates with the number of values that need to be predicted. Meanwhile, in the hidden layer, the optimal number of neurons does not have certain rules [17]. Determining the optimal network configuration often involves a try and error approach [18].

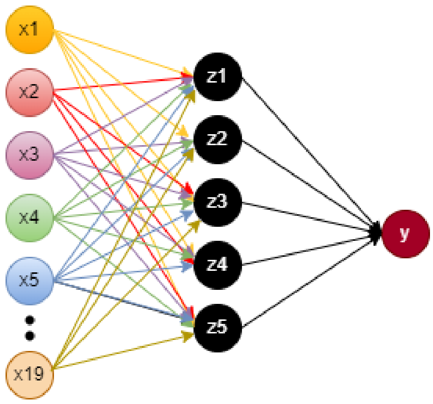

Figure 9 ANN Architecture

In this study, there are 19 neurons in input layer as a representation of 19 facial features. There is one neuron in output layer as a representation of pain and no pain. Where the value of this neuron will be 1 for pain and 0 for no pain. Meanwhile, in the hidden layer, four variations in the number of neurons are given to form 4 ANN models as shown in Tabel 5

Table 5 ANN architecture

	Number of Neuron		
	Input layer	**Hidden layer**	**Output layer**
model_1	19	5	1
model_2		10	
model_3		15	
model_4		20	

Model evaluation

Model evaluation is done by testing the model's ability to classify. Evaluation can be done by making a confusion matriks. The confusion matrix is a concept in machine learning that contains information about the actual classification results and predictions made by a classification system [19]. This confusion matrix can calculate the accuracy, precision, and recall of the model. Accuracy is comparing all data that is correctly predicted with the total data [19]. Precision is the ratio between the amount of data correctly predicted as positive to the total number predicted in the positive class. The recall compares the number of correctly predicted positive classes with the total number of classes in the positive class[20]. These three parameters can be calculated using the equation [21[:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} x\ 100\%$$

$$Precision = \frac{TP}{TP + FP}\ x\ 100\%$$

$$Recall = \frac{TP}{TP + FN}\ x\ 100\%$$

while:

TP (True Positive) = (total positive data that are classified as correct)

TN = True Negative (total negative data classified as accurate)

FP = False Positive (total positive data that are classified as wrong)

FN = False Negative (total negative data classified as wrong)

RESULTS AND DISCUSSION

This study produced 4 ANN models with four variations on the number of neurons in the hidden layer. Each model is evaluated by calculating three performance parameters. Table 6 displays the confusion matrix from the evaluation results on model_1. Colored writing indicates TP or the correct classification results according to the class. In the training set, 2097 frames were correctly predicted as pain, and 5897 frames were correctly predicted as a non-pain class. There are 788 frames of no pain, which are classified as pain by the system. Or in other words, as many as 8.5% of the no-pain frames are misclassified. There are 1218 frame pains that are classified as no pain by the system, or 25% of frame pains that are misclassified.

This test shows that model_1 can classify pain and no pain with an overall accuracy of 80% for training and test data. The difference is, in the test data, the level of precision is 3% higher, and the recall and F1-score are 2% higher than the training data

Table 6 Performance of model_1

			Actual Class		**Accuracy**	**Precision**	**Recall**	**F1-Score**
			Pain (1)	***No Pain (0)***				
Training set	**Predicted class**	***Pain (1)***	2097	788	**80%**	**73%**	**63%**	**68%**
		No Pain (0)	1218	5897				
Test set	**Predicted class**	***Pain (1)***	1350	456	**80%**	**75%**	**65%**	**70%**
		No Pain (0)	729	3465				

Table 7 shows the evaluation results on model_2. In the training set, there were 2228 frames correctly predicted as pain and 6047 frames correctly predicted as a non-pain class. There are 638 frames of no pain, which are classified as pain by the system. Alternatively, in other words, as many as 7% of the no-pain frames are misclassified. The system classified 1218 pain frames as no pain or 22% of wrongly classified pain frames.

This test shows that Model_2 can classify pain and no pain with an overall accuracy of 83% for training and test data. In testing

 https://doi.org/10.25077/jitce.7.01.49-55.2023

using test data, the level of precision is 1% higher for precision, recall, and F1-Score compared to training data.

Table 7 Performance of model_2

			Actual Class		Total	Accuracy	Precision	Recall	F1-Score
			Pain (1)	***No Pain (0)***					
Training set	**Predicted class**	***Pain (1)***	**2228**	638	2866	83%	67%	79%	72%
		No Pain (0)	1087	**6047**	7134				
Test set	**Predicted class**	***Pain (1)***	**1412**	378	1790	78%	83%	68%	73%
		No Pain (0)	667	**3543**	4210				

Table 8 shows the evaluation results on model_3. In the training set, there were 2286 frames correctly predicted as pain and 6116 frames correctly predicted as a non-pain class. As many as 6% of no pain frames are incorrectly classified as pain, and 21% of pain frames are misclassified.

Table 8 Performance of model_3

			Actual Class		Total	Accuracy	Precision	Recall	F1-Score
			Pain (1)	***No Pain (0)***					
Training set	**Predicted class**	***Pain (1)***	**2286**	569	2855	84%	80%	69%	74%
		No Pain (0)	1029	**6116**	7145				
Test set	**Predicted class**	***Pain (1)***	**1478**	379	1857	84%	80%	71%	75%
		No Pain (0)	601	**3542**	4143				

This test shows that model_3 can classify pain and no pain with an overall accuracy of 84% for training and test data. In testing, using test data was 1% higher for recall and F1-Score than training data

Table 4 shoes he evaluation results on model_4. In the training set, there were 2446 frames that were correctly predicted as pain and 6195 frames which were correctly predicted as a non-pain class. As many as 5% of no-pain frames are incorrectly classified as pain, and 18% of pain frames are misclassified.

Table 9 Performance of model_4

			Actual Class		Total	Accuracy	Precision	Recall	F1-Score
			Pain (1)	***No Pain (0)***					
Training set	**Predicted class**	***Pain (1)***	**2446**	490	2936	86%	83%	74%	78%
		No Pain (0)	869	**6195**	7064				
Test set	**Predicted class**	***Pain (1)***	**1562**	329	1891	86%	83%	75%	79%
		No Pain (0)	517	**3592**	4109				

This test shows that model_4. can classify pain and no pain with an overall accuracy of 86% for training and test data. In the test using 1% higher test data for recall and F1-score compared to training data.

From the results of this evaluation, it can be compared how the number of nodes in the hidden layer affects the performance of the four models. The graph shows a comparison of the four models for each parameter. From the graph, it can be seen that the model with 20 neurons has a higher performance of all parameters.

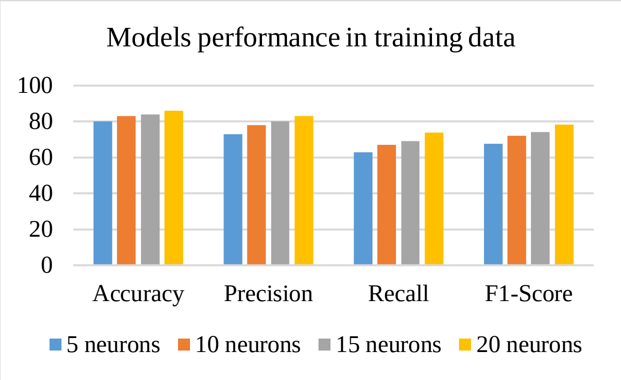

Figure 10 Models performance based on training data

From the results of this evaluation, it can be compared how the number of nodes in the hidden layer affects the performance of the four models. The graph shows a comparison of the four models for each parameter. The graph shows that the model with 20 neurons has a higher performance of all parameters.

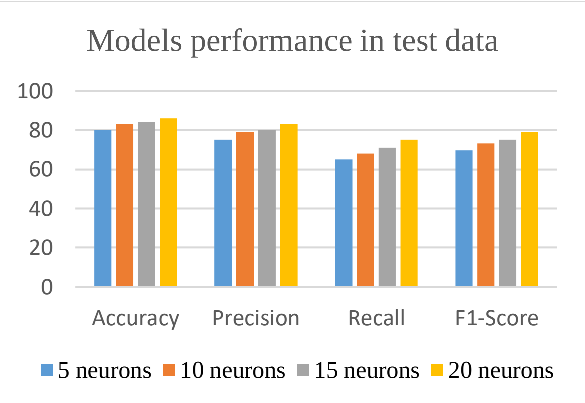

Figure 11 Models performance based on test data

From the Figure 10 and Figure 11, it can be concluded that, both on training data and test data, the lowest performance is on model_1 with five neurons, and the highest is on model_4.

CONCLUSION

A total of 19 geometric features, namely triangles, and lines, can be used to detect pain. It was found that a classification model could be built with the highest accuracy of 86% or with an accuracy of calculating the F1-score of 79%. The number of neurons in the hidden layer affects accuracy, precision, and recall. The more the number of neurons in the hidden layer, the more accurate the resulting level of accuracy. The highest accuracy of the training data is found in the number of hidden layers of 20 neurons. Further studies will be carried out to find and analyze the maximum number of hidden layers that will give the optimum performance. The study will also analyze the effect of the number of training and test data and the influence of parameter and hyperparameter values.

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