A Combination Of Support Vector Machine And Inception-V3 In Face-Based Gender Classification

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***Abstract*— Differences in human facial structures, especially those recorded in a digital image, can be used as an automatic gender comparison tool. This research utilizes machine learning using the support vector machine (SVM) algorithm to perform gender identification based on human facial images. The transfer learning technique using the Inception-v3 model is combined with the SVM algorithm to produce six models that implement polynomial, radial basis function (RBF), and sigmoid kernel functions. The results obtained are models with excellent performance, as seen from the lowest values of accuracy = 0.852, precision = 0.856, recall = 0.852, and the highest values of 0.957, 0.957, and 0.957. This combination also produces a model with excellent reliability, where the probability of overfitting or underfitting obtained is below 1%.**

***Keywords*— gender identification, inception v3, machine learning, kernel function, support vector machine**

I. INTRODUCTION

Based on facial structures such as eyes, lips, and nose, we can identify a person's gender by simply looking at a picture [1]. To automatically identify gender, artificial intelligence, especially machine learning, is one of the tools often applied in human face recognition research [2].

The conclusion found in many studies in human face recognition using machine learning is that the feature extraction process on digital images cannot be said to be simple [3]. Transfer learning using a pre-trained model is one alternative solution to tackle this problem, especially using a Convolutional Neural Network (CNN) model [4]. As one of the pre-trained CNN models, Inception-v3 can extract digital image features automatically and transfer the results can be transferred to a machine-learning algorithm for the classification process [5]. We are interested in combining the Inception-v3 model and the support vector machine (SVM) algorithm, using polynomial, radial basis function (RBF), and sigmoid kernel functions, in facial image-based gender classification.

Recent research on facial image-based gender classification we found included: a gender classification using the logistic regression, support vector machine, K-nearest neighbors, naive-Bayes, and decision trees with a FaceNet Inception network embedded facial image, where the average accuracy obtained from this research is 92.084% [6], an emotion, age group and gender classification using the convolutional neural network model with cropped facial image, where the gender classification shows an excellent performance with an accuracy value of 96.65% [7], and the gender prediction using a combination of Inception V3 network and support vector algorithm, where the results show that this combination gave an accuracy value of 93.61% [8]. These results indicate that combining the convolutional neural networks and machine learning algorithms has an excellent performance in classifying human gender based on an input of facial images.

SVM was chosen as a combination of the Inception-v3 because this algorithm has high flexibility, especially in the kernel functions' selection and determining the hyperparameters used in each kernel function [9]. Several studies have shown the different performances of polynomial, RBF, and sigmoid kernel functions in various classification problems, such as DDoS attack detection [10], facial data recognition [11], and scintillation detection [12].

We transfer the feature extraction from the Inception-v3 model to the SVM algorithm as a dataset. After building six models based on the selection of polynomial, RBF, and sigmoid kernel functions and the values of hyperparameter γ, we compare the accuracy, precision, and recall from all the models. The model reliability assessment used is the difference in value between the evaluation of training and testing data to analyze overfitting or underfitting possibility in each model.

II. METHODS

A. *Support Vector Machine*

In SVM classification, non-linearly separable data can be transformed into a higher dimension using a kernel function (kernel trick) [17]. To improve the performance and efficiency of the prediction results, we can adjust the hyperparameters in kernel functions (such as polynomial, RBF, and sigmoid) formula [18].

The polynomial kernel function has hyperparameters γ (gamma constant), r (kernel Constanta), and p (polynomial degree) to adjust the flexibility of the classification results. Equation (1) shows how to use these hyperparameters in a polynomial kernel function [19]:

$$K_{Polynomial} = (\gamma\, x_i\, x + r)^p \tag{1}$$

The RBF kernel function is one of the kernel functions that is often used in classification research using the SVM algorithm, where this kernel has a hyperparameter γ (gaussian sigma) used in the following equation (2) [20]:

$$K_{RBF} = exp(-\gamma\ |x_i - x|^2) \quad (2)$$

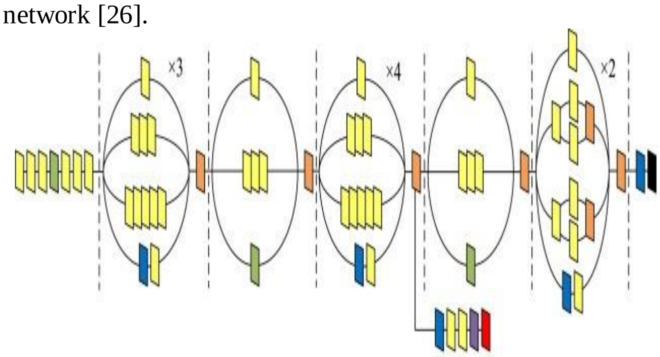
The sigmoid kernel function is a kernel function that is also often used in classification using the SVM algorithm, where this kernel has hyperparameters γ (input data scale parameter) and c (mapping threshold shift parameter). Equation (3) shows how to use these hyperparameters in a sigmoid kernel function [21]:

$$K_{Sigmoid} = tanh(\gamma\ x_i\ x + c), \gamma > 0 \quad (3)$$

In this research, several references to research results that have implemented these kernel functions into classification using data in the form of digital image feature extraction results. Research using polynomial kernels in coffee fruit classification based on feature extraction results using the Hue Saturation Value (HSV) model shows quite good performance with accuracy and f-score values of 78% [22]. Research using RBF kernels in stroke disease classification based on CT Scan image feature extraction results using the Gray-Level Co-Occurrence Matrix (GLCM) method shows a good performance with accuracy and recall values of 82.22%, the precision value of 82.23% and F1-Measure value of 82.27% [23]. Another study on the classification of metallurgical properties of metal pellets based on the results of digital image feature extraction using the GLCM method showed that the sigmoid kernel function used in the SVM algorithm was able to produce an accuracy of up to 98% [24].

B. Inception V3

Inception V3 (IV3) is a networks based on pre-trained CNN algorithms that can be used to extract image features based on previous training data sets [13]. With a combination of nine and twenty-two Inception modules-Convolutional Layers, IV3 uses them to process the features from an image [14]. As one of the variations of GoogleNet, IV3, based on 7x7 convolution factorization, consists of 2 or 3 convolution layers with 3x3 dimensions [15]. Inception-v3 is a model trained on Google's ImageNet, with Figure 1 showing the architecture of this network [26].



Note = Convolution, = MaxPool, = AvgPool, Concat, = Fully Connected, = Dropout, = Softmax

Fig. 1 Architecture of Inception-v3

In the Inception-v3 model, there are several convolutional layers and pooling layers formed in parallel, with size variations of 3×3, 1×3, 3×1, and 1×1. The purpose of these layers is to reduce the number of digital image feature parameters where the final result is 5X5 dimensions containing 2048 features [27]. These results indicate that combining the convolutional neural networks (and their pre-trained models) and machine learning algorithms (especially the support vector machine algorithm) has an excellent performance in classifying human gender based on an input of facial images.

As a reference regarding the process and results of feature extraction using the Inception-v3 model, the author refers to lung image classification research that utilizes the Inception-v3 model in extracting digital image features. This research shows that the feature extraction transferred to the SVM algorithm obtained an overall accuracy value of 85.70%, sensitivity value of 92.96%, and specificity value of 79.83%. These results demonstrate that when applied in the classification process utilizing the SVM technique, the feature extraction from Inception-v3 can generate good performance [28]

C. Dataset

The data we use in this research is in the form of 23243 images of female faces and 23766 images of male faces obtained from the kaggle.com website [29]. We then select the best 1000 images, with a composition of 700 images as training data and 300 images as testing data.

Figure 2 shows the sample used as training data, which consists of 350 images of female faces and 350 images of male faces. As testing data, we also used 150 photos of male and female faces, with sample images shown in Figure 3.

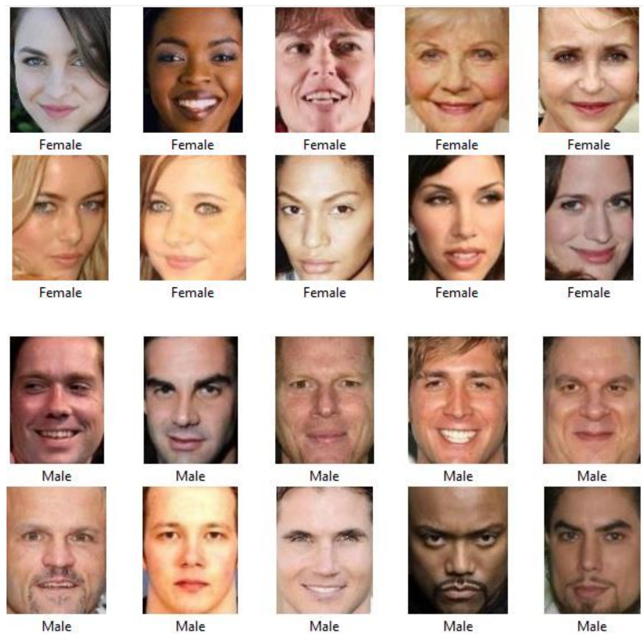


Fig. 2 Training Data Sample

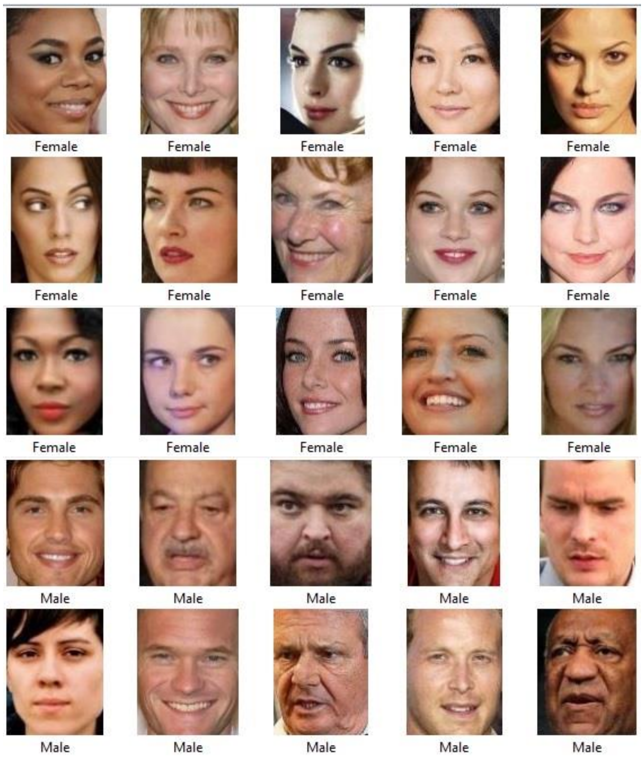


Fig. 3 Testing Data Sample

D. Classification Model

This research uses the Inception-v3 to extract the training and testing images' features and train them as a dataset. The 2048 features, labeled N0, N1,..., and N2047, will be produced by this feature extraction and used as labels in the SVM algorithm's classification process. The gender classification performed in this study has two class targets, namely Female and Male. The Female class is a group of images classified as female gender, while the Male category consists of the male gender. We designed six SVM models by utilizing polynomial, RBF, and sigmoid kernel functions, where each model uses different hyperparameter values, as shown in Table I.

TABLE I
CONFIGURATION OF CLASSIFICATION MODEL

Model	Kernel	Hyperparameter
SVM-Poly	Polynomial	$\gamma = 0.01$, $r = 1$, $p = 1.5$
SVM-RBF	RBF	$\gamma = 0.02$
SVM-Sig	Sigmoid	$\gamma = 0.03$, $c = 0.09$
SVM-Poly2	Polynomial	$\gamma = 0.02$, $r = 1$, $p = 1.5$
SVM-RBF2	RBF	$\gamma = 0.01$
SVM-Sig2	Sigmoid	$\gamma = 0.02$, $c = 0.09$

The classification process begins by reading the training dataset obtained from the Inception-v3 feature extraction results, and then classification is carried out by finding a hyperplane that can separate the data into the Female class (positive class) and Male class (negative class) using the following equation (4) [30]:

$$min\ (w,b,s) = \frac{1}{2}(w,w) + c + \sum_{i\in s^+}^{n} \varepsilon_i + C - \sum_{i\in s^-}^{n} \varepsilon_i \quad (4)$$

The result of equation (4) is then inputted into equation (5) to produce a classification to calculate the margin values of the Female and Male data classes [31]:

$$f(x) = w^T x + b \quad (5)$$

If $w^T x + b \geq 1$, then Female class else Male class

E. Evaluation

In this study, we evaluate the classification outcomes using training and test data using both 10-fold and 20-fold cross-validation. We use the accuracy, precision, and recall values to test the performance of each model, using formulas as shown in equations (7) to (9) [32].

$$Accuracy = \frac{TP+TN}{Predicted+Actual} = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

$$Precision = \frac{TP}{Positive\ Predicted} = \frac{TP}{TP+FP} \quad (8)$$

$$Recall = \frac{TP}{Negative\ Predicted} = \frac{TP}{TP+FN} \quad (9)$$

TP is the total female genders predicted correctly, and FN is the number of male genders incorrectly predicted. TN is the number of male genders (the negatives class data) predicted correctly, and FP is the female gender (the positives class data) incorrectly predicted [33]. These values are presented in a Confusion matrix table, as shown in Figure 4, to illustrate the relationship between the actual and the predicted data.

		Predicted	
		Female	Male
Actual	Female	True Positive	False Negative
	Male	False Positive	True Negative

Fig. 4 Confusion Matrix Table

III. RESULTS

The results obtained in this study are Inception-v3 feature extraction statistics for training and test data, cross-validation values using 10-fold and 20-fold, and evaluation in the form of models that produce the best performance. The results of Inception-v3 feature extraction are 2048 features, labeled N0 to N2047 for each of the 700 training data and 300 test data processed. Table II shows the five earliest and latest samples of feature extraction results for the training data, with feature values at N0, N1, N2046, and N2047. Table III shows the five earliest and latest samples of feature extraction results for the test data, with feature values at N0, N1, N2046, and N2047.

TABLE II
SAMPLE FROM TRAINING DATA FEATURE EXTRACTION

Data	No	N1	…	N2046	N2047
1	0.416	0.372	…	0.292	0.325
2	0.347	0.555	…	0.382	1.233
3	0.374	0.446	…	0.133	0.385
4	0.212	0.475	…	0.146	0.370
5	0.246	0.516	…	0.285	0.429
…	…	…	…	…	…
696	0.560	0.589	…	0.508	0.430
697	0.491	0.374	…	0.215	0.280
698	0.817	0.878	…	0.049	0.410
699	0.263	0.435	…	0.208	0.401
700	0.265	0.283	…	0.311	0.179

TABLE III
SAMPLE FROM TESTING DATA FEATURE EXTRACTION

Data	No	N1	…	N2046	N2047
1	0.208	0.302	…	0.064	0.344
2	0.150	0.419	…	0.026	0.262
3	0.098	0.632	…	0.067	0.184
4	0.278	0.472	…	0.432	0.591
5	0.177	0.388	…	0.076	0.702
…	…	…	…	…	…
296	0.342	0.351	…	0.355	0.899
297	0.101	0.495	…	0.069	0.105
298	0.655	0.583	…	0.088	0.409
299	0.747	0.503	…	0.109	0.311
300	0.492	0.646	…	0.066	0.446

Using 10-fold and 20-fold cross-validation, the classification results of each six models used in this study are evaluated, with the results in the form of a confusion matrix table. Table IV below shows the training data classification evaluation for all models, while Table V shows the testing data evaluation results.

TABLE IV
CONFUSION MATRIX FOR TRAINING DATA

Model	Class	Positive Prediction		Negatives Prediction	
		10-Fold	20-Fold	10-Fold	20-Fold
SVM-Poly	Female	328	333	22	17
	Male	18	20	332	330
SVM-RBF	Female	310	307	40	43
	Male	40	36	310	314
SVM-Sig	Female	290	285	60	65
	Male	27	35	323	315
SVM-Poly2	Female	333	327	17	23
	Male	23	21	327	329
SVM-RBF2	Female	279	281	71	69
	Male	28	38	322	312
SVM-Sig2	Female	284	275	66	75
	Male	17	22	333	328

TABLE V
CONFUSION MATRIX FOR TESTING DATA

Model	Class	Positive Prediction	Negatives Prediction
SVM-Poly	Female	141	9
	Male	9	141
SVM-RBF	Female	128	22
	Male	14	136
SVM-Sig	Female	121	29
	Male	9	141
SVM-Poly2	Female	141	9
	Male	4	146
SVM-RBF2	Female	116	34
	Male	8	142
SVM-Sig2	Female	128	22
	Male	12	138

We then use equations (7) to (9) to get the results of the 10-fold and 20-fold cross-validation evaluation of training data on the SVM-Poly, SVM-RBF, SVM-Poly2, SVM-RBF2, and SVM-Sig2 models such as the overall accuracies, precisions and recalls value shown in Table VI. We also use the same equations to get the results of the testing data evaluation for all models shown in Table VII.

TABLE VI
EVALUATION FOR TRAINING DATA

Model	Accuracy		Precision		Recall	
	10-Fold	20-Fold	10-Fold	20-Fold	10-Fold	20-Fold
SVM-Poly	0.943	0.947	0.943	0.947	0.943	0.947
SVM-RBF	0.886	0.937	0.886	0.937	0.886	0.937
SVM-Sig	0.876	0.887	0.879	0.887	0.876	0.887
SVM-Poly2	0.943	0.847	0.943	0.850	0.943	0.847
SVM-RBF2	0.859	0.857	0.864	0.860	0.859	0.857
SVM-Sig2	0.881	0.861	0.889	0.870	0.881	0.861

TABLE VII
EVALUATION FOR TESTING DATA

Model	Accuracy	Precision	Recall
SVM-Poly	0.94	0.94	0.94
SVM-RBF	0.88	0.881	0.88
SVM-Sig	0.873	0.873	0.873
SVM-Poly2	0.957	0.957	0.957
SVM-RBF2	0.86	0.871	0.86
SVM-Sig2	0.887	0.888	0.887

We then calculate the average value of all the results of the training data evaluation (the 10-fold and 20-fold) from each model for the final value of the models' evaluation, shown in Table VIII.

TABLE VII

AVERAGE VALUE OF TRAINING DATA EVALUATION

Model	Accuracy	Precision	Recall
SVM-Poly	0.944	0.944	0.944
SVM-RBF	0.886	0.871	0.886
SVM-Sig	0.866	0.869	0.866
SVM-Poly2	0.939	0.939	0.939
SVM-RBF2	0.852	0.856	0.852
SVM-Sig2	0.871	0.879	0.871

From the results shown in Tables 7 and 8, we then calculate the difference value (Δ value) of the accuracies, precisions, and recalls generated by each model. To see the possibility of overfitting or underfitting in the models, we use Table IX as the tabulated results of these calculations.

TABLE IX

DIFFERENCE OF MODEL EVALUATION VALUE

Model	ΔAccuracy	ΔPrecision	ΔRecall
SVM-Poly	0.004	0.004	0.004
SVM-RBF	0.006	-0.01	0.006
SVM-Sig	-0.007	-0.004	-0.007
SVM-Poly2	-0.018	-0.018	-0.018
SVM-RBF2	-0.008	-0.015	-0.008
SVM-Sig2	-0.016	-0.009	-0.016

A positive Δ value means that there is a possibility of underfitting happens, while a negative Δ value shows the overfitting possibility. All Δ values from Table IX show results below 1%. This result shows that all the generated models have good reliability.

IV. CONCLUSIONS

From the results of this research, we conclude that the Inception-v3 model facilitates the process of extracting features from digital images, compared to using manual methods. We can use the 2048 features from Inception-v3 feature extraction as a dataset for the SVM's classification process, with excellent performance results. The accuracy, precision, and recall shown in the evaluation of training data and test data, which are 0.852 and 0.86, are solid proof for this statement. The resulting models in this study have good reliability, shown in the delta (Δ) values between the classification's evaluation of the training and testing data, which is below the value of 1%. The delta values indicate that all the models only have the possibility of overfitting or underfitting below 1%. The different values of hyperparameter γ also affect the SVM classification performance. We can see from the accuracy, precision, and recall values between SVM-Poly and SVM-Poly2, SVM-RBF and SVM-RBF2, and SVM-Sig and SVM-Sig2 that the difference in the value of γ by 0.01 is enough to affect the change in these values. Overall, from the results of this study, we can conclude that the combination of Inception-v3 and the SVM algorithm, specifically using polynomial, RBF, and sigmoid kernel functions, can be applied to perform human face-based gender classification with excellent performance and reliability.

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