Classification technique for real-time emotion detection using machine learning models

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ABSTRACT

This study aimed to explore models to identify a human by using face recognition techniques. Data were collected from Cohn-Kanade dataset composed of 398 photos having face emotion labeled with eight emotions (i.e., neutral, angry, disgusted, fearful, happy, sad, and surprised). Multi-layer perceptron (MLP), support vector machine (SVM), and random forest were used in model accuracy comparisons. Model validation and evaluation were performed using Python programming. The results on F1 scores for each class in the dataset revealed that predictive classifiers do not perform well for some classes. The support vector machine (RBF kernel) and random forest showed the highest accuracies in both datasets. The results could be used to extract and identify emotional expressions from the Cohn-Kanade dataset. Furthermore, the approach could be applied in other contexts to enhance monitoring activities or facial assessments.

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1. INTRODUCTION

Emotion recognition is being actively researched in various fields, including computer science, neurology, biology, psychology, and medicine, both in theory and in applications [1]. It is a crucial step towards machines that understand human behavior. Anger, disgust, contempt, fear, joy, sadness, neutrality and surprise are the eight basic human emotions. There are several ways to recognize human emotions using various human behavioral features such as speech, electroencephalogram (EEG) data, and facial images [2]. Machine learning is a topic of study that focuses on how to turn empirical data into useable models using computational techniques. Traditional statistics and artificial intelligence groups gave birth to the machine learning discipline [3]. Machine learning can be divided into three types, namely supervised learning (learning with data to teach), unsupervised learning (learning without teaching data), and reinforcement learning (learning according to the environment).

Emotion recognition from video requires the functions of face recognition. Face recognition is a technology capable of matching a human face from a digital image or a video frame against a database of faces, typically employed to authenticate users through ID verification services, and it works by pinpointing and measuring facial features from a given image. Face recognition can be applied in many contexts, of which we list a few. (i) Access Control: The size of the group of people who need to be identified in many access control applications, such as office access or computer logon, is rather modest. Face images are also captured in natural settings, such as frontal faces with indoors lighting for office door access control [4].

(ii) Security: Today more than ever, security is a top priority for airports, airline employees, and customers. Face recognition technology-based airport security systems have been installed in several airports throughout the world [5] and smart home security uses IoT and face recognition. A motion detection camera captures an image of the person in front of the door and then real-time face recognition is done using local binary pattern (LBP). If the person's image matches one of the homes members, then the door will unlock, else doorbell will ring. If an intruder tries to break in, then an alarm will be raised via both short messaging service (SMS) and Email containing images of the intruder, and will be sent to the homeowner [6]. (iii) Image database investigations: Searching image databases of licensed drivers, benefit recipients, missing children, immigrants, and police bookings. General identity verification: Electoral registration, banking, electronic commerce, identifying newborns, national IDs, passports, and employee IDs. (iv) Surveillance: Surveillance using facial recognition systems, like security applications in public spaces, has a low, if not non-existent, degree of customer satisfaction. Face recognition systems for large-scale monitoring are difficult to deploy due to free lighting conditions, face angles, and other factors [7] for example in the live security systems of all public and private places and in multiple other uses. Such real-time security uses internet protocol closed-circuit television (IP CCTV) cameras for surveillance. Face recognition is a way of identifying or confirming an individual's identity using their face. Face recognition systems can be used to identify people in photos, videos, or in real-time. Face recognition is important in biometric security [8], [9].

Emotion detection is used to achieve various goals. (i) In robotics: to design smart collaborative or service robots that can interact with humans [10]–[12]. (ii) In marketing: to create specialized adverts based on the emotional state of the potential customer [12]–[14]. (iii) In education: to improve learning processes, knowledge transfer, and perception methodologies; [15]–[18] and (iv) in entertainment industries: to propose the most appetizing content [19]–[21]. From the example, Emotion detection is important in terms of interaction with humans. This is important, as the systems can adapt their responses and behavioral patterns according to the emotions of the humans and make the interaction more natural.

This study investigated suitability of model types in identifying human faces, by comparing the performances of several alternative machine learning algorithms: multi-layer perceptron (MLP), k-nearest-neighbors (k-NN), support vector machine (SVM), decision tree, and random forest. In this approach, we used to label facial expression images from the Cohn-Kanade dataset, which contains more than a thousand photos, with our data preparation module to analyze the experimental results. The proposed model determines the label call for facial expression based on an image.

2. ALGORITHM

2.1. Multi-layer perceptron

The definition of the MLP architecture includes choosing the number of layers, the numbers of hidden nodes in each layer, and the objective functions as shown in Figure 1. However, another approach utilized in this paper allows to control all the connections between the layers and to delete some of them if there are no connections between the nodes. MLPs can resolve issues that are not linearly separable because they are built to approximate any continuous function. Pattern classification, recognition, prediction, and approximation are the main use cases for MLP [22].

2.2. Random forest

Random forest (RF) is a data mining technology that can be used to solve classification and regression tasks. Classification accuracy has substantially increased because of the use of an ensemble of trees and voting to determine the class call. Random vectors are used to create these ensembles. One of the random vectors is used to create each tree. Classification and regression trees make up an RF.

The output of the trees is analyzed to determine classification calls. The RF prediction is determined by a majority vote. Because overfitting does not occur for large RFs, the generalization error approaches a threshold as trees are added to the RF [23].

2.3. K-nearest-neighbors

One of the most basic machine learning methods is the k-nearest-neighbors (k-NN) algorithm. It is simply predicated on the notion that "Objects that are 'near' each other have similar features as well. So, if we know the characteristics of one object, we can predict the characteristics of its next-door neighbor." The k-NN technique is a refinement of the nearest neighbor technique. It works on the principle that any new instance can be categorized by the majority vote of its "k" neighbors. Neighbors can be categorized using the formula where k is a positive integer, usually a small number [24].

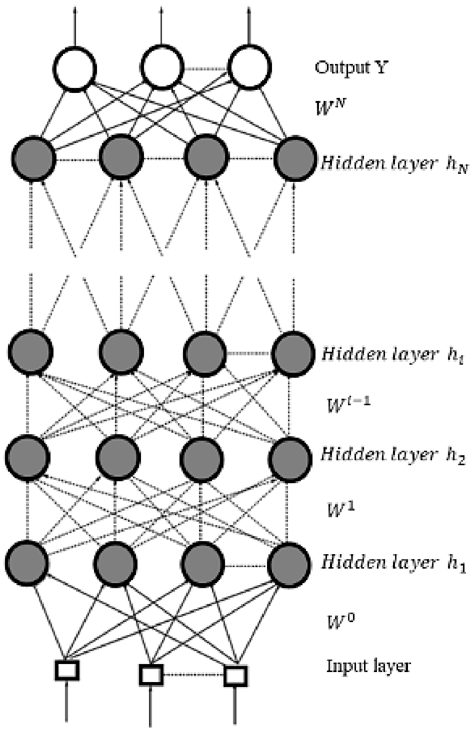

Figure 1. Multi-layer perceptron algorithm

2.4. Support vector machines

Support vector machines (SVMs) are a relatively new type of algorithm that is receiving attention because of its amazing accuracy and capacity to handle big, high-dimensional datasets. Lighting analysis, haptic data prediction, and financial forecasting are just a few of the disciplines where the SVM algorithm has been used. SVM can be used for incident detection, traffic speed and flow prediction, journey time, traffic flow and speed prediction, and eye movement detection, among other things [25].

2.5. Decision tree

The decision tree is constructed with a supervised learning algorithm and can be used to solve both regression and classification tasks. The algorithm creates rules using training data, and the learned classifier can be represented as a tree structure. It has a root node, internal nodes, and leaf nodes, much like any other tree representation. The condition for the attributes is represented by the internal nodes, the branches represent conditional outcomes, and the leaf nodes have class labels assigned. Start at the top of the root node and work your way to the leaf nodes using the if-else rules at branching nodes, to arrive at a categorization. The class label for your classification problem is that of the leaf node you settle on [26].

The implementation of decision tree in Python's Sklearn library was used in this study. We developed a decision tree using selected attributes at each level to be the root node. The selected attribute in the same class was identified using the Gini index, Gaining knowledge, and Chi-square.

2.6. Naïve Bayes

The naive Bayes algorithm generates a simple probabilistic classifier that calculates a set of probabilities by counting the frequencies and combinations of values in a data set. The procedure employs Bayes' theorem and assumes that all variables are unaffected by the class variable's value. Although this conditional independence assumption is rarely true in real-world applications and is thus regarded as naive, the method learns swiftly in a variety of supervised classification problems [27], [28].

3. METHOD

3.1. Data collection

The dataset was created by combining photos from the Cohn-Kanade dataset, which contains more than a thousand photos, with our data preparation module. The Cohn-Kanade (CK) database was made public in order to encourage research on detecting individual facial expressions automatically. The CK database has since grown in popularity as one of the most extensively used testbeds for algorithm creation and evaluation [29].

This dataset contains 398 photos of faces and eight emotion labels including neutral, angry, disgusted, fearful, happy, sad, and surprised as shown in Figure 2. Then, 68 points showing facial expression were extracted from each face photo using the egg-face model pre-trained by Keras (Keras is a deep learning framework for Python that simplifies modeling with deep learning).

Figure 2. Examples from the CK + database

3.2. Data formatting

The facial behavior of 210 adults was recorded using two hardware-synchronized Panasonic AG-7500 cameras. Participants were between 18 and 50 years old, 69% female, 81% Euro-American, 13% African-American, and 6% from other groups. Participants were instructed by an experimenter to perform a series of 23 facial representations [30].

Since each face is recognized as having the same 68 points, the system compares faces based on those points. We currently have 68 * 2 (x and y-axis values), giving us a total of 136 values. Comparing and categorizing these values has a low success rate. This is because the coordinates may vary depending on the size and shape of the face. Therefore, the center of 68 points is defined as the zero point (origin). All vectors are created based on these zero points. The class values associated with the attributes are learned from datasets using machine learning models. Images taken at regular intervals by a computer's camera are immediately marked using the OpenCV library.

3.3. Sampling method

The train_test_split() function in the data science library scikit-learn was used to split the dataset into subsets that minimize the potential for bias in the evaluation and validation process. The data were randomly allocated into two subsets,

– The training set is applied to train, or fit, your model.
– The test set is needed for an unbiased evaluation of the final model.

Using train_test_split(), the dataset for training was 60% and testing had 40%, and we set random_state = 42. train_test_split() returned 4 variables: train_x, train_y, and test_x, test_y. In this way, the train_x data consists of independent variables that match train_y as the dependent variable for model identification (i.e., training). The variable test_x is the independent variable and test_y is the matching dependent variable, used for testing the generated model.

3.4. Machine learning models

There are various classifier type machine learning models. In this paper, the classification models used were random forest, k-nearest-neighbors, support vector machine (ensemble), decision tree, multi-layer perceptron, and Naïve Bayes. All the machine learning models used in this work are listed in Table 1, along with their specific parameter settings [31].

3.4.1. Model validation

Cross-validation is a model validation approach for determining how statistical analysis results generalize to previously unseen data from the same sampled population [32]. In this paper, popular cross-validation approaches, such as random hold-out, were applied (randomly splitting 60 percent of the data into the training set and 40 percent into the test set).

Table 1. Parameters used in machine learning algorithms

Model type	Parameters
Multi-layer Perceptron	solver='lbfgs', alpha=1e-5, hidden_layer_sizes = (8) random_state = 1
Random Forest	n_estimators=100 min_samples_leaf = 1
K-nearest-neighbour	n_neighbors=8 weights = 'uniform' algorithm = 'auto' leaf_size = 30
Support Vector Machine	kernel = 'rbf' gamma= 'scale'
Decision Tree	random_state = 1 criterion = 'gini' splitter = "best" min_samples_split = 2 min_samples_leaf=1
Naïve Bayes	No Parameters

3.4.2. Methods of evaluation

Comparing and determining the optimal model requires evaluating the performance of classifiers. Machine learning algorithms can be measured and verified in a variety of ways. Several evaluation methods are used in this study, including prediction accuracy, recall, precision, and F1 score. All of the models were created using Python, an interpreted general-purpose high-level programming language. Classification Accuracy is what we usually mean when we use the term accuracy. It is the ratio of number of correct predictions to the total number of input samples (1).

$$Accuracy = \frac{\text{TrueNegative} + \text{TruePosittive}}{\text{TruePosittive} + \text{FalsePosittive} + \text{TrueNegative} + \text{FalseNegative}} \quad (1)$$

It works well only if there is an equal number of samples in each class. F1 Score is the Harmonic Mean of precision and recall. The range for F1 Score is the [0, 1] interval. It tells you how precise your classifier is (how many instances it classifies correctly), as well as how robust it is (it does not miss a significant number of instances) [33].

High precision but lower recall gives you extremely good accuracy while missing a large number of instances that are difficult to classify. The greater the F1 Score, the better is the performance of our model. Mathematically, it can be expressed as here,

$$F_1 = \left(\frac{recall^{-1} + precision^{-1}}{2}\right) = 2 \cdot \frac{precision \cdot recall}{precision + recall} \quad (2)$$

F1 Score tries to find a balance between precision and recall.

- Precision is the number of correct positive results divided by the number of positive results predicted by the classifier (3).

$$Precision = \frac{\text{TruePosittive}}{\text{TruePosittive} + \text{FalsePosittive}} \quad (3)$$

- Recall is the number of correct positive results divided by the number of all relevant samples (all samples that should have been identified as positive) (4).

$$Recall = \frac{TruePosittive}{TruePosittive + FalseNegative} \quad (4)$$

4. RESULTS AND DISCUSSION

The goal of this study was to compare the performance of alternative machine learning classifiers in real-time emotion detection. The results from the machine learning algorithms MLP, decision trees, naive

Bayes, k-NN, SVM, and random forest showed that the F1 score, which is the harmonic mean of precision and recall, includes vital and essential information about the classifier performance for each class. As previously stated, the distribution of classes was not balanced. The F1 score findings for each class in the dataset reveal that predictive classifiers do not perform well for some classes. The support vector machine (RBF kernel) and Random Forest showed the highest accuracies in the dataset as shown in Figure 3.

The results also showed performances of the various classifiers on imbalanced datasets from using the random hold-out technique. Various assessment measures, such as Accuracy, Recall, Precision, and F1-score, were used to acquire a better understanding of the model performances. Table 2 shows the calls from MLP, SVM, and Random Forest with the highest macro average of 58% and MLP having the highest weighted average of 76%. Table 3 shows the recall, with MLP having the highest weighted average of 76% and random forest with the highest-class macro average of 55%. The F1 - Score is shown in Table 4. Random forest, with an accuracy of 80%, is the most accurate model for each class, followed by MLP and SVM, both with an accuracy of 78 percent.

Table 2. The precision for all tested algorithms

Class	Precision					
	MLP	Decision Trees	Naive Bayes	K-NN	SVM	Random Forest
anger	0.53	0.50	0.20	0.00	0.00	0.00
contempt	0.00	0.38	0.10	0.00	0.00	0.50
disgust	0.82	0.50	0.40	0.86	1.00	0.89
fear	0.55	0.18	0.33	0.00	1.00	0.60
happy	0.93	0.92	0.92	0.96	0.96	0.93
neutral	0.81	0.82	0.79	0.66	0.70	0.75
sadness	0.00	0.18	0.17	0.00	0.00	0.00
surprise	0.97	1.00	1.00	1.00	1.00	0.97
macro avg	0.58	0.56	0.49	0.43	0.58	0.58
weighted avg	0.76	0.74	0.69	0.63	0.71	0.71

Table 3. The recall for all tested algorithms

Class	Recall					
	MLP	Decision Trees	Naive Bayes	K-NN	SVM	Random Forest
anger	0.44	0.39	0.22	0.00	0.00	0.00
contempt	0.00	0.43	0.43	0.00	0.00	0.14
disgust	0.58	0.38	0.79	0.25	0.58	0.67
fear	0.60	0.20	0.30	0.00	0.10	0.30
happy	1.00	0.82	0.82	0.79	0.93	0.96
neutral	0.92	0.91	0.51	1.00	1.00	0.98
sadness	0.00	0.18	0.18	0.00	0.00	0.00
surprise	0.85	0.91	1.00	0.94	0.97	1.00
macro avg	0.55	0.53	0.53	0.37	0.45	0.51
weighted avg	0.78	0.74	0.59	0.73	0.78	0.80

Table 4. The F1-Score for all tested algorithms

Class	F1 - Score					
	MLP	Decision Trees	Naive Bayes	K-NN	SVM	Random Forest
anger	0.48	0.44	0.21	0.00	0.00	0.00
contempt	0.00	0.40	0.16	0.00	0.00	0.22
disgust	0.68	0.43	0.53	0.39	0.74	0.76
fear	0.57	0.19	0.32	0.00	0.18	0.40
happy	0.97	0.87	0.87	0.86	0.96	0.95
neutral	0.86	0.86	0.62	0.79	0.82	0.85
sadness	0.00	0.18	0.17	0.00	0.00	0.00
surprise	0.90	0.95	1.00	0.97	0.98	0.99
Accuracy	0.78	0.74	0.59	0.73	0.78	0.80
Macro avg	0.56	0.54	0.48	0.38	0.46	0.52
Weighted avg	0.76	0.74	0.62	0.65	0.71	0.74

As with any machine learning algorithm, a large amount of training data is required. Videos with varied frame rates, from various viewpoints, with varying backgrounds, with individuals of various genders, nations, races, and so on must be included in these data. The majority of publicly available datasets, however, are insufficient. They lack racial and gender diversity, as well as represent only a narrow range of emotions. There are two options for dealing with this problem,

– Make your own dataset. This is the most expensive and time-consuming option, but you'll get a dataset that's excellent for your needs.
– Combine a number of different datasets. You can test your solution's performance on a variety of different datasets.

Machine learning algorithms parse data, learn its properties, and then recognize the same data in real life. To produce a correct output, they require human intervention and a large amount of organized training data. The experiment's results were acquired by Dhwani Mehta and colleagues [34]. Random Forest can distinguish emotions and assess their intensity because it can handle both numerical and categorical inputs. RF accuracy ranges from 71% to 96%, depending on the complexity of the detected features. The results in the previous studied [35] was simulated and implemented in MATLAB using Japanese female facial expression (JAFFE) and Mevlana University facial expression (MUFE) databases. The images were greyscale in tiff file format. The study showed that the performance of principal component analysis (PCA)+SVM had a recognition rate of 100% at two instances for JAFFE while MUFE had recognition rate 87% using PCA+SVM [35]. However, Emotion Recognition using only facial expressions is not enough. We can use audio, written expressions from text, and physiology as measured by wearables to assist in classification in order to increase the efficiency and precision of the model.

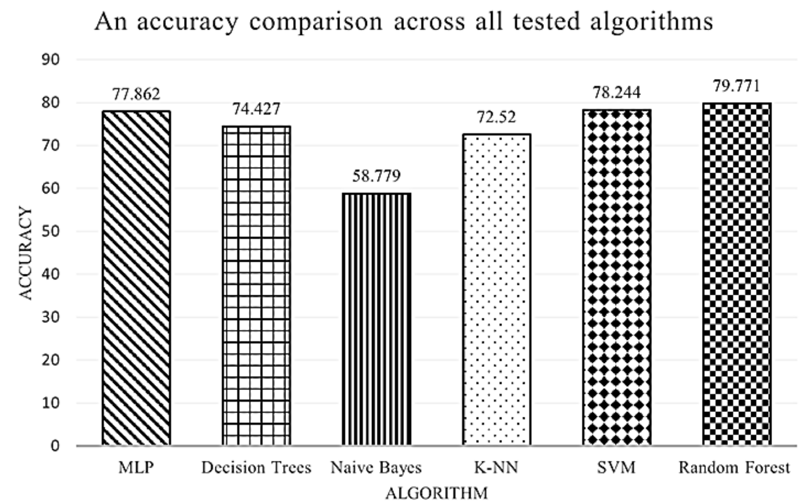

Figure 3. An accuracy comparison across all tested algorithms

5. CONCLUSION

We compared the performances of the MLP, k-NN, SVM, Decision Tree, and Random Forest machine learning algorithms in this work. With our data preparation module, we were able to extract emotional expressions and photographs from the Cohn-Kanade dataset, which contains over a thousand photos. In modern applications we strive to identify eight emotional expressions (anger, contempt, disgust, fear, happy, sadness, surprise, and neutral). A unified roadmap for calling the emotional expressions has been offered in a number of works using deep learning. However, emotion awareness remains a difficult goal for automated algorithms, and the current study supports improving automated calls based on still photos.

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