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FER_ML: Facial Emotion Recognition using Machine Learning

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ABSTRACT

Recently, facial recognition has been one of the most crucial technologies people need. Facial recognition has attracted a lot of the crowd; for example, it has been used in security on most modern devices. Using machine and deep learning, overall performance will be improved, and the identification accuracy will be more precise. We aim to discover how well these algorithms perform in classifying human facial expressions and whether or not we can depend on them. The steps are as follows. First, we embed the images from the dataset, then split the dataset into 70% training data and 30% testing data; after that, we apply five different algorithms: Support Vector Machine, K-nearest Neighbor, Logistic Regression, Naive Bayes, and Random Forest. Support Vector Machine achieved an accuracy rate of 36%, K-nearest Neighbor achieved an accuracy rate of 52.3%, Logistic regression achieved an accuracy rate of 64.2%, and Naive Bayes achieved an accuracy rate of 38.1%. Random Forest achieved an accuracy rate of 51.7%. The dataset used was a cleaned version of the FER13 dataset, which contains 16,780 images divided into five classes (angry, happy, neutral, disgust, and fear). The results show that Logistic Regression proved to be the most accurate classifier among the presented ones, with an F1-Score of 63.8% and an accuracy of 64.2%.

1. Introduction

Facial emotions play a monumental role in our modern-day society. They are constantly used throughout our daily lives whether at school, work, or home they play a vital role in ensuring that our emotions are correctly understood by the person we're interacting with. Facial expressions are one of the most effective methods to convey emotions to another human being[1].

Machine learning has been innovating and pioneering in various fields, from medicine to self-driving cars. One of the latest techniques in recognizing facial emotions is machine learning, which has been making strides in developing facial emotion recognition through various algorithms and equations such as Support Vector Machine (SVM) and Logistic Regression. Automatic facial emotion recognition with machine learning can be used to augment and enhance the effectiveness of almost any field where social interactions and clarity is important such as clearly conveying the patient's emotions to their doctor or the criminal's state of mind to their investigators.

Falsely identifying emotions can lead to many problems, especially in our modern society, where artificial intelligence is prevalent far and wide. For example, in the future, a system might be developed to aid psychiatrists in determining whether the patient's psyche is stable enough to continue living on their own or if it would be necessary for them to be admitted to a mental asylum. An error in the mentioned situation could cause to further damage to the patient's mental state leading to more harm than good. Thus it is crucial to train a precise machine learning model to ascertain the target's emotions.

In this paper, we propose a method to recognize and classify the facial expressions shown in the dataset through a set of machine learning algorithms. We shall discuss previous research done on the topic of facial emotion recognition using machine learning. Then we shall propose the algorithms used in our research and how they function. From then on, we display the results of those algorithms. Finally, we end the paper with the conclusion of our research.

Sign languages are visual-gesture-based languages regarded as the deaf community's mainstream language. Gestures and visual channels are used to communicate in this language [1]. Hand gestures, body movements, and facial expressions are utilized for communicating in sign language. The World Health Organization estimates that 466 million people worldwide suffer from hearing loss, with 34 million children. Over 900 million individuals are expected to experience hearing loss or communication issues by 2050, according to estimates [2]. Almost 121 forms of sign language are used worldwide now [3], with a shortage of sign language interpreters to deal with the diversity. As a result, translation technologies that make the translation process faster and more precise are needed. The first stage in automatic translation is to standardize sign language. Stokoe [4], HamNoSys [5], SignWriting [6], and Gloss Notation are just a few examples of sign language Forms. Facial expressions and body movements are not included in Stokoe's notation. As a result, this sign language is limited and unsuitable for deaf translation. In addition, the HamNoSys form uses a 3D animated avatar to formalize any sign language. However, It does not give a simple way to describe body movements and facial expressions. The SignWriting notation employs highly iconic symbols, which are difficult to decipher using a computer. Gloss notation, on the other hand, is a formal sign language similar to Braille, Morse code, and finger-spelling. It annotates, represents, and explains visual-gestural language sequences based on natural language word labels. This is a simple approach to represent an idea in sign language articulated in natural language. Glossing has received much attention in sign language translation because of its simplicity, expressiveness, and formal representation of sign language [7-9, 3]. For years, machine and deep learning have demonstrated remarkable effectiveness in various application domains.

Several researchers have expressed interest in employing a neural network to translate sign languages using machine translation [10-14]. Neural Machine Translation (NMT) is a modern neural network-based translation technique [15]. It is an end-to-end learning approach for automated translation. It has two parts: an encoder and a decoder. An attention mechanism [16] has recently been developed to allow a neural network to pay attention to only a specific area of an input sentence while creating a translation comparable to human translations to improve the learning process. Even though NMT approaches are more successful than traditional machine translation approaches, most neural-based studies disregard the linguistic features of sign language. They believe there is only a one-to-one correspondence between signs and spoken words.

Furthermore, most modern neural networks concentrate on translating from gloss sign language to natural language. However, completely automating translation systems in both directions requires the second direction from natural language to gloss sign language. The following are the contributions of this paper. First, it provides sequence-to-sequence deep learning models that translate gloss sign language to natural text using a transformer. Second, it introduces a deep learning model that translates natural language text to sign language gloss using a sequence-to-sequence approach. Third, this study evaluates the proposed models on the ASLGPC12 corpus [17, 18]. Different metrics, such as BLEU (Bilingual Evaluation Understudy) and ROUGE (Recall-Oriented Understudy for Gisting Evaluation), are used to evaluate the performance outcomes. In addition, the best model of the experiments is compared to previous research on the same corpus. The remainder of the paper is laid out: The second section provides some background information on sign languages. Section 3 discusses several related works. Section 4 introduces the proposed approach. The experimental results are discussed in Section 5. Finally, Section 6 concludes the paper.

3. Related Work

Numerous articles and research papers have been published regarding the various characteristics of facial emotion recognition using machine learning.

In [2], the authors divided their system into three phases. Phase one: face detection using Haar Cascades, phase two: normalization, and phase three: uses a Convolutional Neural Network (CNN) on the FER 2013 database, which includes seven different expressions. The CNN architecture used in the system comprises four convolutional layers, four pooling layers, and two fully connected layers. The dataset was split into training and testing data, measuring 80% and 20% of the total dataset, and yielded an accuracy rate of 70%.

In [3], the author proposed a two-level CNN framework that removes the background from the picture through a skin tone detection algorithm [4] in the first level. The second level detects facial features through an edge detection filter. Once the filter detects all 24 facial features, an EV matrix that holds the distance between each face part is generated. The datasets used are the Cohn-Kanada expression dataset, multiple datasets from the internet [5][6], and the author's pictures. The final dataset was divided into 70% training and 30% testing images and achieved an accuracy of 96%.

In [7], the authors proposed a system that classifies the facial emotions of elders, and they detect the effects of becoming old and its resulting changes on facial emotions. The authors used Viola Jones with Haar Features to extract the faces from the images. They use the Gabor filter to get the attributes of the face so they can detect neutral, happy, and sad states. The approach uses a Multiclass Support Vector Machine as a classifier and the Lifespan Image dataset to train and test the model. They achieved an accuracy of 90.32%, 84.61%, and 66.6% when detecting the neutral state, happiness, and sadness, respectively, in the elderly. In the other age group, we got an accuracy of 95.24%, 88.57%, and 80% while detecting the neutral, happiness, and sadness states.

In [8], the authors propose a three-step process to recognize facial emotions. First, they use the Viola-Jones algorithm to detect the face in the picture. In the second step, they apply the HOG algorithm to extract the feature from the face. Third step, they classify the extracted features with support vector machine (SVM), K-nearest neighbor (KNN), and multilayer perceptron (MLP). The dataset used in this experiment is the CK+ dataset, which consists of 634 different images of adults between the ages of 18 to 50 displaying 8 different emotions: neutral, anger, contempt, disgust, dear, happiness, sadness, and surprise. They used 10-fold Cross- Validations to evaluate each model. After training, KNN achieved an accuracy rate of 79.97%, MLP achieved an accuracy rate of 82.97%, and SVM achieved an accuracy rate of 93.89%.

Vikrant Doma and Matin Pirouz In their research article "comparative analysis of machine learning methods for emotion recognition using EEG and peripheral physiological signals"[9] , Which was published in 2020 in a data magazine titled "Journal Of Big Data" the articles goal is to apply different machine learning algorithms and create a comparison between them depending on the results of each of them such as their accuracy and the percentage of error and to improve their results by applying PCA a dimensionality reduction method[10] , They tested the selected algorithms on a database entitled DEAP[11], which is a freely available EEG archive containing analyzes of various human brain states with emotions divided into 32 Biosemi [12] files distributed over 48 channels recorded at a frequency of 512 Hz in addition to that this archive is The output of merging 3 different databases from Switzerland, Holland and England , They chose SVM, Naive Bayes, Decision Trees, Logistic Regression, KNN and LDA algorithms. After the tests, the average accuracy of these algorithms ranged between 55% and 77%, and the F1 score ranged between 70% and 86%. According to the authors, no algorithm outperformed the others by a big difference.

According to the "Facial Expression Recognition with In- consistently Annotated Datasets," a lecture from a book series "Lecture Notes in Computer Science," specifically in the book "Computer Vision - ECCV 2018"[13], in which Jiabei Zeng, Shiguang Shan, and Xilin Chen addressed the problems they face in the field of Facial Emotion Recognition using Machine Learning specifically problems and obstacles related to datasets, one of the most important of these problems is the variation and difference in human expressions, even if the emotion is common between one person and another. Still, the expression of the face can differ, and this is due to several reasons, such as different cultures and living environments. And after they studied various databases such as CK+, MMI, and Oulu-CASIA, they came up with Inconsistent Pseudo Annotations to Latent Truth "IPA2LT," a 3-step framework used to build FER models that deal with this discrepancy from one database to another. The first step in their framework is to train machine annotators, and the second step is to predict the pseudo label' happy,'' sad' or' angry.' The last step after that is to train the end-to-end Latent Truth Net (LTNet) to discover the latent truth. They tested their invention on a database called CIFAR-10, which contains 60,000 small images divided into ten categories. They chose 10,000 images to use in the test and left the rest to the learning process and then synthesized three pieces of inconsistent annotations for the training samples 20%, 30%, and 40% of the correct labels. They put it in comparison with other models that were trained using famous learning algorithms such as CNN and State of Art; from their point of view, their discovery is suitable as a preliminary solution to a problem that has not been addressed much. Rather, it is superior to the model educated in the State of Art method.

[14], It has been Sounded in fresh research that people's emotions can be proclaimed and used in many fields like learning and medicine. Precision can be different according to the number of data collected, the stability of the database, the specifying system, and the number of emotions studied. Recognition of emotions is not a static process that makes every action according to one person from another different. So, an accurate study of these emotions is needed to gain good communication. Emotions can impact almost all of our conversation styles, like poses, stances, and expressions. Even breathing or Stress level. Feelings always hit hard when it comes to the face. It's the most obvious one to be impacted. We can declare that a multi-modal way will improve accuracy using deep learning.

In [15], With the increasing demands of applications related to entertainment, commerce, physical and psychological health, and education, interest in emotional computing is growing. As a result, several emotion-sensitive HCI systems have been developed recently, even though the ultimate solution has yet to be proposed for this research field. Emotional recognition is taking most of the interest, as the paper focuses on implementing different techniques to be compared to enhance the prediction results of facial emotions. They implemented the SVM and Deep Boltzmann Machine (DBM) Classifiers for the prediction. The dataset used is from FERA 2005. They also used a fusion method to enhance the performance of the system.

[16] The technology of analyzing the face has been rapidly researched and studied, and one of its applications is face recognition. It has been attracting people a lot recently. People use it in face detection, expression identification, robotic interactions, and video games. A new technology named LEMHI is used to enhance the MHI "motion history image" by using face areas to increase value in calculation and learning. Furthermore, using MHI will give us a single frame fed into the CNN program for learning. The difference here is that face recognition is static, but the expressions are more of a dynamic process. However, the motion history has proven quite useful in this case because it could effectively get dynamic data to solve the problem of facial expression analysis.

Shivam Gupta proposed in [17] the importance of facial emotions as it has many applications in computer vision. Facial expressions recognition also enhances human-robot interactions and reactions, and in trying to simulate it, The authors used static and real images to detect the facial reactions. They used Cohn-Kanade Database and Extended Cohn-Kanade (CK+) database [18], which uses 640 x 640 pixels for the static images and a webcam for the real-time ones. They used the HAAR filter to detect the faces; once detected, it can be cropped and processed to detect the characteristics of the face. They use different approaches, and the SVM has achieved the best results with an accuracy of around 91%. Also, other related work in [19-27] has been proposed in recent years to address machine learning and its application in different fields.

3. Proposed Approach

The main objective of this research paper is to test a set of different machine learning algorithms to determine their accuracy, success, or failure in determining the feeling that a person displays from his facial expressions only. Our research paper can be classified as a deductive research paper, where this type of research begins on a theory or belief that already exists and begins to build on it to reach a final result and discover whether this belief is true or false. In our case, the belief that our research is based on is that the machine learning algorithm has shown results ranging from very good to excellent in recognizing emotions through facial expressions; this is according to what was published by many types of research, some of which we discussed in the related work section. In this research, we will rely on quantitative research methods and experiments to reach the final results although we have relied on cross-sectional time horizon data in this research, which means that these data were captured and collected in the same time period and not on intermittent time periods. After that, we shall discuss the sampling strategy used in this research, and we relied on it on two main criteria, the first being the ease of access to these samples, such that they are available on reliable and free sources. The second criteria is that the dataset should be large because it is illogical to conduct tests on a small number of 10 or 20 photos, for example. Finally, we shall discuss the way we collected the data used in the research, and given that the target data are images and fall under the quantitative data, we searched for data that matched the two criteria mentioned above and found a data set of images of faces expressing different emotions on Kaggle blog [29] titled "FER13 Cleaned Dataset"[30]. The data set contains 16,780 black and white pictures divided into 5 classes (angry, happy, neutral, disgust, fear). After we embedded the images, we used a data sampler to divide this data into train and set data, the train data was 70% of the actual number of images in the data set and the other 30% are the testing data.

4. Methods

In this section of the research, we will discuss in some detail the machine learning algorithms that we will test in this research, such as SVM, RF, KNN, Logistic Regression, and Naive Base.

4.1. Logistic Regression

One of the most famous and significant algorithms in this science for his distinguished ability to find possibilities and learn new data classifications based on different types of data, it comes under the Supervised Learning techniques and is very similar to Linear Regression. The resulting drawing from using this algorithm is an s-shaped drawing from which the maximum and minimum points can be determined.Its mathematical equation can be extracted from the equation of the straight line and the Linear Regression. Still, the latter cannot be used to solve classification problems.

$$y = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_nx_n \quad (1)$$

$$\log\left[\frac{y}{1-y}\right] = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots + b_nx_n \quad (2)$$

4.2. Support Vector Machine (SVM)

An important algorithm because of its ability to solve various types of problems, whether classification or regression. The main objective of this algorithm is to find the best line separating the data so that we can classify future data correctly, and it creates so-called hyperplanes using absolute points and vectors. There are two types of it; the first is linear, which is used when the available data is separable using a straight line directly. In contrast, the second type is nonlinear, and as it is clear from the name, this type is used when the available data is not separable by a straight line. One of the important terms that must be understood to understand how this algorithm works is support vectors. This term expresses the closest points of each available class in the data to the line separating the available classes. Another term is the hyperplane, which is the best line between the available classifications, and its dimensions are determined depending on the Features available in the data. If it is 2, the hyperplane is a straight line; if it is 3, it is two-dimensional.

$$\vec{X} \cdot \vec{w} - \mathrm{c} \geq 0 \quad (3)$$

putting $-c$ as b, we get (4)

$$\vec{X} \cdot \vec{w} + \mathrm{b} \geq 0 \tag{5}$$

$$\mathrm{y} = \begin{cases} +1 & \text{if } \vec{X} \cdot \vec{w} + \mathrm{b} \geq 0 \\ -1 & \text{if } \vec{X} \cdot \vec{w} + \mathrm{b} < 0 \end{cases} \tag{6}$$

4.3. Random Forest (RF)

The random forest algorithm is a supervised learning algorithm that works on classification and regression problems like the SVM. This algorithm combines multiple classifiers, specifically a set of decision trees, so that data is entered into more than one classifier, and the classification result is determined based on a vote applied to the results of these classifiers. This algorithm is considered one of the good algorithms because it needs less training time than other algorithms, and its results are mostly accurate even with giant datasets. Additionally, this algorithm can produce good results even if some data is lost from the data set. The algorithm works with four main steps; the first is to choose a number of K points from the selected training data, then we build decision trees based on the selected points, and then we specify the number of decision trees we want to combine, and finally, we repeat the first and second steps until we get the results from these trees that are using the Entropy Equation to calculate how well the features of the data set is well divided.

$$E(S) = -p_{(+)}\log_{(+)} - p_{(-)^{\log p}}^{(-)} \tag{7}$$

4.4. K-Nearest Neighbor (KNN)

K-Nearest Neighbor is a supervised machine-learning algorithm that can be used for classification and regression. It assumes the value of the data according to the similarity between the new and current data. It compares the new data to its neighboring point to determine its value. This algorithm is one of the easiest machine learning to understand and implement, and it is very effective in dealing with nonlinear data. Even though it is simple to implement, it does require a great deal of memory because it stores all the training data. It is also very susceptible to pointless features and the size of data. The first phase of this algorithm is to choose the value of K, which represents the number of neighbors chosen to compare with the new data to classify it. Next, calculate the distance between each neighbor and the new data point through any method such as Euclidean or Manhattan distance. Then the value of the data will be chosen according to the value of its nearest neighbor

$$d(\mathbf{p}, \mathbf{q}) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2} \tag{8}$$

$$d(x, y) = \sum_{i=1}^{n} |x_i - y_i| \tag{9}$$

4.5. Naive Bayes (NB)

Naive Bayes is a supervised machine learning algorithm used to solve classification problems. It is most commonly used in text classification. It is called "Naive" because it assumes that a specific feature is unaffected by the other features. It is called "Bayes" because it is built upon the Bayes theorem, which states that the probability of an event depends on previous information related to the event. Naive Bayes is one of the simplest machine learning algorithms, and it is very useful when facing a multiclass classification problem. Still, it can lead to some false solutions due to the assumption that features are unrelated. The first step in Naive Bayes is to turn the data into a frequency table to determine how often each class occurs, then calculate the probability of each class, then use Bayes theorem to calculate the posterior probability for each class, and the class with the highest probability is the solution.

$$P(A \mid B) = \frac{P(B|A) \cdot P(A)}{P(B)} \quad (10)$$

5. Experimental Results

In this section, we display the results acquired by the algorithms SVM, KNN, Naive Bayes, Logistic Regression, and Random Forest on the FER13 Cleaned Dataset, which contains images of the emotions anger, happy, neutral, disgust, and disgust. Several evaluation metrics are used to evaluate the performance of the classification. The most common metrics include accuracy (ACC), precision (PREC), sensitivity (recall) (REC), specificity, and f-score (F1). They are calculated as follows:

$$Acc = \frac{TP+TN}{TP+FP+TN+FN} \quad (11)$$

$$prec = \frac{TP}{TP+FP} \quad (12)$$

$$Rec = \frac{TP}{TP+FN} \quad (13)$$

$$prec = 2 * \frac{Prec*Rec}{PrecRec} \quad (14)$$

Where TP, TF, FP, and FN indicate the true positive, true negative, false positive, and false negative respective

Table 2
Summary of the results After Pre-Processing

Model/Measures	AUC	CA	F1 Score	Recall	Precision
LR	0.857	0.642	0.638	0.642	0.635
KNN	0.732	0.523	0.498	0.523	0.513
RF	0.728	0.517	0.498	0.517	0.505
NB	0.685	0.381	0.422	0.381	0.492
SVM	0.653	0.360	0.375	0.360	0.449

Table 3
Naive Bayes Confusion Matrix

Actual Predicted	Angry	Happy	Neutral	Disgust	Fear	Total
Angry	224	176	104	254	84	842
Happy	177	1033	183	533	161	2087
Neutral	182	324	366	265	161	1298
Disgust	8	30	6	46	9	99
Fear	95	143	58	178	262	736
Total	686	1706	717	1276	677	5062

Table 4
KNN Confusion Matrix

Actual Predicted	Angry	Happy	Neutral	Disgust	Fear	Total
Angry	337	325	128	9	43	842

Happy	168	1629	199	27	64	2087
Neutral	193	571	473	5	56	1298
Disgust	13	49	15	17	5	99
Fear	108	315	117	7	189	736
Total	819	2889	932	65	357	5062

Table 5
Logistic Regression Confusion Matrix

Actual Predicted	Angry	Happy	Neutral	Disgust	Fear	Total
Angry	373	164	184	16	105	842
Happy	96	1694	196	31	70	2087
Neutral	123	245	798	17	115	1298
Disgust	21	20	11	29	18	99
Fear	124	109	129	19	355	736
Total	737	2232	1318	112	663	5062

Table 6
Random Forest Confusion Matrix

Actual Predicted	Angry	Happy	Neutral	Disgust	Fear	Total
Angry	227	342	210	1	62	842
Happy	139	1544	314	1	89	2087
Neutral	124	473	616	1	84	1298
Disgust	15	44	21	12	7	99
Fear	97	263	160	0	216	736
Total	602	2666	1321	15	458	5062

Table 7
SVM Confusion Matrix

Actual Predicted	Angry	Happy	Neutral	Disgust	Fear	Total
Angry	452	91	115	17	167	842
Happy	593	836	281	43	334	2087
Neutral	543	213	319	12	211	1298
Disgust	33	12	13	13	28	99
Fear	356	103	69	8	200	736
Total	1977	1255	797	93	940	5062

6. Conclusion

Facial emotion recognition plays a vital role in many fields, and with machine learning algorithms, accurate recognition of emotions is possible. In this paper, we proposed a facial expression recognition using machine learning classifiers (SVM - Naive Bayes - Logistic Regression - KNN - Random Forest) on the dataset that consists of 16,780 images divided into five classes (Happy - Anger - Neutral - Disgust - Fear). The paper focuses on comparing the different classifiers to obtain the best results. The goal was to achieve the best accuracy rate possible, and the logistic regression classifier has proved that it has the highest accuracy among the others, with the accuracy of 64.2%. This score was achieved by training on the split 70% training and 30% testing dataset.

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