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Robust Face Recognition System Based on Deep Facial Feature Extraction and Machine Learning

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ABSTRACT

Facial Recognition is a common challenge in research for security applications. Wide-ranging applications of this technology include biometrics, security data, access to controlled locations, smart cards, and surveillance systems. A practical approach to identifying individuals depends on factors such as partial face occlusion, illumination, age, expression, makeup, and poses. These complex face recognition variables affect most face recognition systems. In this paper, we propose a deep transfer learning for facial features based on the pose and illumination variations of celebrities' faces in a free environment for face recognition. The new approach that combines deep learning methods for feature extraction with machine learning classification methods. Also, studies the performance of the pre-trained model (VGGFace2 with ResNet-50 model weights) for feature extraction with a Multilayer Perceptron Classifier (MLP), Decision Tree, and Bootstrap Aggregation (Bagging) to perform classification. The convolution neural network has lately achieved excellent advancement in facial recognition. The outcome indicated that VGGFace2 with MLP obtained more precision and provided the best results (Accuracy, F-measure, Recall, and Precision). The results for all metric for the proposed model is 99%. The benchmark for this model is a dataset of 105 people's faces.

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1. Introduction

The data security is becoming increasingly important as computer and network technology advances. Personality identity is essential for the system's security to be ensured [1]. National security, banking, e-commerce, law, and other sectors require accurate Recognition. Human beings are born with biological characteristics. Their one-of-a-kindness and outstanding qualities, which are impossible to duplicate, provide the crucial element of recognized proof [2], [3]. As a result, the biometric recognition-based personal ID system garners the most attention due to its better security, validity, and dependability. It has begun to permeate many aspects of our life. Image Processing has a wide range of uses in today's technologically assisted environment, including video surveillance, crowd analysis, behavior analysis, teleconferencing, and identification via person recognition using different biometrics [4]. For example, Fingerprint recognition [5], iris recognition [6], palmprint recognition [7], DNA recognition [8], and ECG recognition [9]. Face Recognition has become fundamental to the biometrics examination heading due to its ease in gathering face images, communicating many personal data characteristics, high Recognition, and originality [10]. Image processing, machine learning, biological science, computer technology, neural networks, and other topics are all used in face recognition [11]. Face recognition technology has recently acquired enormous traction due to rapid advancements in several disciplines, and its application area has gradually expanded. Currently, it's primarily used in security, financial, and public security systems, among other things [12]. Face recognition is a crucial test experienced in the multidimensional visual model investigation and is a hot examination zone. Perceiving the human face is a problematic and essential skill to master since it exhibits changing characteristics such as emotions, illumination, position, disguise, age, and hairstyle, among others. Ageing causes permanent changes to the human face as well [13]. Face recognition is non-trivial and challenging due to these variables. Face recognition is defined as giving a computer system the capacity to quickly and accurately detect and recognize human faces in films or pictures [12]. Numerous algorithms and Strategies have been devised to enhance face recognition performance.

Recent advances in image classification, such as face recognition, have effectively leveraged deep learning-based techniques to encode feature representations [14], [15]. Deep learning (DL) can be employed in biometrics to discuss essential biometric information and make advancements when performed by multiple authentication and recognition systems text box

1.1. Motivation

The main issue with the face recognition system's feature representation technique is that it uses an inferior way of representation to extract features for a particular biometric characteristic [16]. Among the most critical stages in image classification is feature extraction. Preserving the most crucial data is what is meant by "extracting features," which is necessary for the classification. Several feature extraction techniques, including independent component analysis (ICA), principal component analysis (PCA), and local binary patterns (LBP), have been proposed for application in biometric systems [2]. DL, especially the convolution neural network (CNN), has become the dominant feature extraction method in recent years [6,7]. There are various strategies for using CNN [17]. The first is to thoroughly learn the model. In this instance, the architecture pre-trained models are applied and then trained using the dataset. In situations where the dataset is enormous, the second method uses transfer learning with features from previous CNN that were taught [18]. The current system optionally suffers from following The drawbacks:

- High dimension features The domination of features extracted when being very high potentially produces overlaps features.
- Change Illumination: The face image has significant problems when changing the illuminations at the capturing image. That affected the image descriptors or features extraction process.
- Face emotion: The details of the image with the facial emotion make a high difference at each capture

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1.2. Contribution

In this paper, we apply the CNN approaches with pre-trained models for face classification accuracy by analyzing the face recognition performance. Here, the pre-trained models (VGGFace2 with ResNet-50 models) are used for feature extraction, and then multilayer perceptron classifier (MLP), decision tree, and bootstrap aggregation (bagging) are used for classification. Eventually, CNNs can be employed through transfer learning by saving the (convolutional) base in its initial form and then employing its outputs to feed the classifier. The pre-trained model is used as a specified (feature extraction mechanism) in circumstances the database is little or when the issue is similar to one to be classified [19]. The contributions of the proposed methods can be summarized in the following:

- Accurate features: The proposed model uses the new approach of feature extraction with highly accurate features of data objects. The VGGFace2 with ResNet-50 models are used together to extract features has high accuracy with high correlation to the data object.
- Anti-change Illumination: The proposed framework of the system produced an integrated system that resists the change of lighting in the image so that it extracts important characteristics from the image that gives high accuracy by describing and retrieving the image.
- Resistant Face emotion: The proposed model focused on extracting stills and strong details of the face image therefore; it is resistant to changing emotion of the face.

1.3 Evaluation Strategy

To evaluate the proposed strategy, the face dataset from Kaggle [20] is used. The evolution metrics that are used in comparing and testing the validity of the proposed system are accuracy, precision, recall, and f1-score. The proposed model is tested over different machine-learning methods. Moreover, it is compared with the number of recent students in face recognition techniques.

2. Literature survey

Since 1990, active research has been conducted in face recognition due to its many helpful applications. In this study, we show that landmarks obtained using a face recognition model are automatically transformed to mask a celebrity identity dataset. The face recognition model uses reconstructed faces as input to create feature embedding. Wang et al. [10], in the proposed work present the landmarks retrieved using a facial recognition model are transformed to automatically mask a celebrity databased that was initially unmasked. The network EdgeConnect is used to transfer learn reconstruction phase. They used Pins-Face database with remove the low resolution image. The number of image that used is 8000 for 105 classes. The accuracy is 91%. Ali et al. [21] This study compares the results of classification techniques such as random forest, logistic regression, KNN, and SVM based on deep feature extraction techniques (Inception and Squeeze_Net). The Pins-Face database was used. The result shows that the accuracy of logistic regression is 94.8%. Saib et al. [22] proposed several schemes for identifying masked faces. The main features of prominent faces were extracted using the Histogram of Gradients method (HOG) and pre-trained models (VGG16 and Mobile-NetV2). Support vector machines (SVM) and a SoftMax layer are used as classifiers. The researcher is used Pins-Face database. The results show the model MobileNetV2 is 96.8%. M. S. Bilkhu, Gupta, et al. [23] demonstrated a facial emotion recognition system (FER). It employed the (cascade regression tree) technique for feature extraction and compared the outcomes of machine learning algorithms for classification: NN, SVM, and logistic regression. The limitation of this work is the use of SVM, but it is inefficient due to the high diminution problem. Miakshyn, Oleksandr et al. [24] in this study modified the architecture of (OpenFace) by classifier learning approach and the architecture facilitation. The Pins-Face database was used to train the network. The result of the research on Pins-Face is 85.5%. Chen Qin et al. [25] proposed a deep CNN-based recognition algorithm. Face detection, alignment, and feature extraction were all included in the algorithm. For the Extraction of facial features, the deep CNNs VGG16 were used. The studies used pictures from five different angles (right, left, overlook, look up, and front). The results of the experiment demonstrated that the algorithm was successful at recognizing faces in a variety of indoor situations. Chandran, Pournami, et al. [11] proposed a system for missing child identification. The robust CNN-based on DL for face features extraction and the MSVM classifier for identifying various child classes are combined. This system is evaluated with the DL model which is trained with the depiction of features of children's faces. removing the softmax from the VGGFace model to improve performance and extracting CNN image features to train SVM. The proposed system performance is evaluated utilizing images of children taken in different lighting and noise environments and images taken at various ages. Guo et al. [26] presented a facial recognition system using SVM as a classifier and the CNN for feature extraction. They trained CNN using optimization approaches to improve its performance. The model requires less training time and improves its rate of Recognition. Usga et al. [27] This study used a (photo ID) as a dataset to determine the identification of a person. Age progression parameters for facial recognition systems are present in photo ID datasets using two different types of datasets, namely (the primary for electronic identity cards and the tertiary IvS) datasets, to test the proposed technique. The core dataset comprises manually gathered information through questionnaires, whereas the second dataset is made available to the general public. We only use one data for the training process: a photo ID that can currently only be used to recognize faces. As a result, we apply the pretrained VGGFace2 model and (AM-Soft max loss) as a loss function to refine the data during training.

3. Material and Method

This section discusses the materials and methods used in this paper. One of the biggest biometric challenges is face identification. The given research delves into the training process as well as the methodology of the proposed facial recognition system. Face recognition is an essential and a great performer based on the application due to technological features and qualities. The proposed face recognition system is divided into three steps: Image acquisition and pre-processing feature extraction and classification methods. For specific datasets, Pins-Face-Recognition is used to test the suggested system's performance. All images in the dataset are cropped to hold the face area. The face images are colored and include faces in various angles, lighting, emotions, makeup or without. The approach of feature extraction VGGFace2 with ResNet-50 models was utilized. Finally, a Multilayer Perceptron Classifier (MLP), Decision Tree, and Bootstrap Aggregation (Bagging) to perform classification. Fig. 1 shows the suggested method.

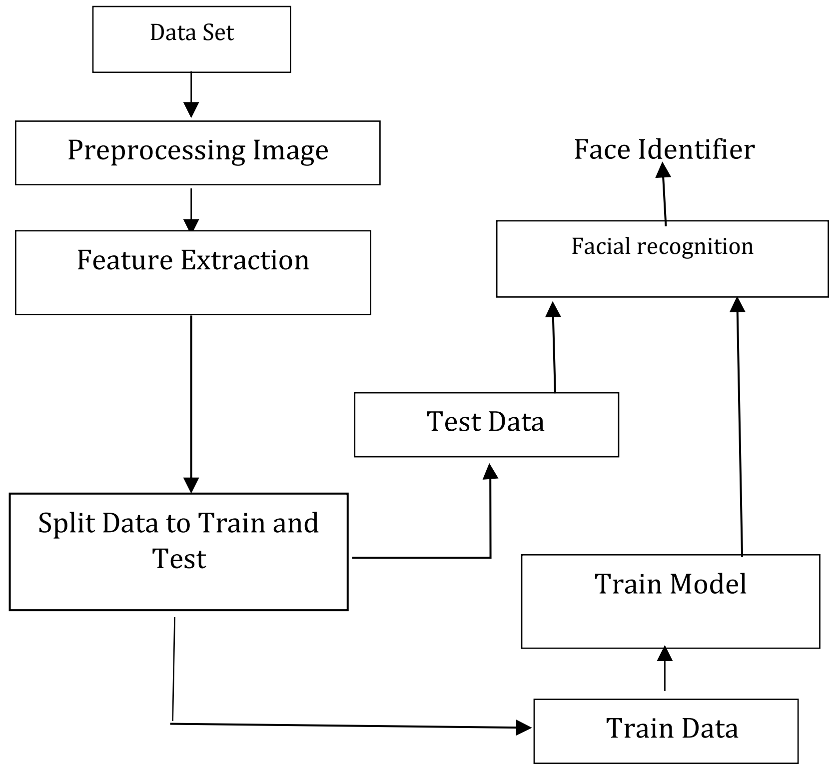

Fig. 1 – Proposed Methodology Process for face recognition.

3.1 Feature Extraction

Feature extraction reduces the resources required to describe vast volumes of data. Furthermore, feature extraction from specific data was one of the crucial issues for practical machine learning applications. There are various applications for feature extraction, particularly in computer vision, which uses algorithms to separate the elements or shapes in an image. The data is then transformed into a simplified representation of the original information when an algorithm's input data is so large that it is difficult to process it. It is anticipated that producing a surplus in data may lead to high computation and processing [16], [28]. It is important to analyze a face first to extract its features, which are simply numerical descriptions of the face. The features are then extracted, and this process is referred to as feature extraction. This paper used the pre-trained VGGFace2 with ResNet-50 model weights feature extractor to generate face features as feature extraction techniques from original face images and used them in the classification stage. Face representation, which has grown in importance in recent face recognition research, significantly impacts the convolution neural network's ability to recognize faces. CNNs are used to classify images in the majority of published works in four different ways: by training network weights from the scratch (typically only when available a very large dataset), by fine-tuning the weights of a pre-trained model (produces a similar outcome to training from the scratch and might done in smaller datasets), and utilizing unsupervised pre-training to establish initial weights before training the model CNN, and by using a pre-trained model CNN (at times named an out-of-box CNN or off-the-shelf) as a features extractor. The latter approach typically blends hand-crafted characteristics with features extracted from the CNN to train a more effective and accurate classifier. VGGFace and VGGFace2 are the two primary models for facial Recognition. The name "VGGFace" refers to a group of facial recognition models developed by Oxford University's Visual Geometry Group (VGG), and tested on computer vision benchmark datasets. In the 2015 publication, Omkar Parkhi described the VGGFace model, which was subsequently given a name. The research contributed by detailing the process for producing a considerable training dataset necessary to train current CNN's-based facial recognition systems to overcome the enormous datasets used by Google and Facebook to train their models. The development of deep CNNs for facial recognition systems like face identification and verification is then based on this dataset. They first describe the procedure for training a face classifier, which recognizes people's faces using a soft-max activation in the output layer. Then, this layer is eliminated, leaving a look embedding a vector features representation as the network's output. The model is then further trained through fine-tuning to increase the Euclidean distance between the vectors generated for different identities and decrease the gap between the vectors generated for the same identity. The network architecture uses a deep CNN in VGG-style, with the fully connected layer in the network's classifier end and blocks of (convolutional layers) with tiny kernels and the ReLU activations.

3.2 Classification

Over the last decade, the number of artificial intelligence (AI) based applications significantly raised, as certain emerging machine learning algorithms and technologies. Since then, machine learning has matured enough to enable its usage in various fields, from computer vision to machine-type communications [29]. A necessary, but not sufficient condition for the effective use of machine learning (especially deep learning) methods is the availability of large amounts of training data [30].

The classifier has been fed the extracted features from pre-trained VGGFace2. four classifications are applied to compare the classifier's performance (MLP, DT, and Bagging) are used for classification. The machine learning methods are briefly explained.

- Multilayer Perceptron Algorithm (MLP)

The object's feature vector is regarded as input, while the object's class is treated as output. The multilayer perceptron output layer is the neuron, often known as the rationale unit of the threshold [31]. It may be considered a logistic regression classification approach in which the data is first processed via a trained nonlinear algorithm. The algorithm converts the data supplied into a domain where it may be linearly distinguished. The hidden layer represents the intermediate layer of the neural network. A single middle layer is required to present MLPs as a consistent approximation. In a multilayer perceptron, there may be more than one sequential layer. When a three-layer network is considered, input is supplied at the first layer, the last layer is given the output, and the hidden layer is regarded as the middle layer. The input data is fed into the input layer, and the output layer produces the result. Equation 2 calculates the prediction value of MLP

$$\mathrm{Y} = \sum_{j=1}^{n} w_{ij}\, x_i + b_i \qquad (1)$$

$$Y_i' = \frac{1}{1-e^{-Y}} \qquad (2)$$

Where: x_i is the input value of the ith, w are the weights matrix, and b is a bias value.

- Decision Tree Algorithm (DT)

The Decision Tree algorithm (DT) can be utilized in many scenarios and is surprisingly powerful for such a straightforward algorithm [2]. It requires little data preparation and can even use empty values. DT concentrates on learning simple decision rules deduced from the data and assembles them into a set of (if_then_else) decision rules. DT is the classification method of calculation based on (entropy and information gain). The entropy function calculates the uncertainty in data illustrated in (Eq.1). To calculate the difference of the entropy for data, compute information gain (I) as shown in Equation 3 [2]

$$E(T) = \sum_{i=1}^{m} -p(q_i).\, log\, (p(q_i)) \qquad (3)$$

$$I = E(T) - \sum_{v\in T} p(v)E(v) \qquad (4)$$

Where (q) = a binary label (0 - 1), Where (v) = a sub-set data, T is current data, and p(x) = proportion of (q label).

- Bootstrap Aggregation Algorithm(bagging)

A bagging Algorithm is an ensemble meta-estimator that fits basic classifiers one at a time to random subsets of the initial database, then combines (aggregates) each prediction (either through vote or average) to get the final prediction [2]. By introducing randomization to the process of building a black-box estimator (such as a decision tree), a meta-estimator of this kind can often be used to lower the estimator's variance. A bagging classifier is a robust statistical approach for estimating a number from a dataset that is bootstrapping. It takes the original dataset and divides it into numerous subsample datasets, each with its mean value. The mean value of all the mean sub-samples is then used to calculate the dataset's final amount. The aggregation Bootstrap Algorithm (Bagging) is a highly effective ensemble approach. An ensemble is a method that combines the predictions of many ML algorithms to provide the most accurate results than any single model. Bootstrap is a generic technique for reducing the algorithm's large variances. Bagging is a paradigm in which numerous "weak" learners are simultaneously trained to solve the same problem and then aggregated to get better results.

4. Result and Discussion

This section describes the dataset, evolution metrics and results

4.1 Dataset

The face dataset in [20] consists of 17,534 human faces of 105 celebrities collected from Pinterest. All images in the dataset are cropped to preserve the face region. The face images were taken in different poses, under other lighting conditions, from different angles, with emotions, and with or without makeup. Fig. 2 illustrates the samples of the face dataset

Fig. 2 – Sample of Person's faces in the pins dataset [20].

4.2 Evaluation Metric

Four evaluation metrics of the confusion matrix are used: F- measure (F1-Score) is used to evaluate a test's accuracy by balancing the usage of precision and recall [32]. By employing this metric, more realistic estimates of performance may be obtained (precision and recall). The metrics are shown as follows in equations (5,6 and 7):

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$F1-score = 2.\frac{Precision.\ Recall}{Precision+Recall} \quad (7)$$

Where *TP* is the true positive and *FP* is the false positive and *FN* is false negative

4.3 Results

This part explains the results of applying the pre-trained VGGFace2 model with ResNet-50 model weights for Extracting Features and (MLP, DT, and Bagging) machine learning algorithms for classifying these features. The dataset was split into (70%) for training and (30%) for testing. Table 1 illustrates the comparative results.

Methods	**Precision %**	**Recall %**	**F1-measure %**	**Accuracy %**
MLP	99 %	99 %	99 %	99 %
Bagging	92 %	91 %	93 %	94 %
DT	73 %	74 %	71 %	72%

Table 1 – Result of MLP, Bagging, DT with VGGFACE2.

As can be seen in the table above after testing the machine learning methods, MLP achieves the best result with 99%, while bagging and DT achieve 94% and 72%, respectively. The effective ensemble approach. An ensemble is a method that combines the predictions of many ML algorithms to produce the most accurate results compared to a single model. Bootstrap is a general method to reduce the large variances of the algorithm. The MLP and bagging archive have the best performance in terms of accuracy because the feature extraction model has high compatibility with machine learning methods. The DT depends on the entropy of the information input to the model and therefore has low performance.

To compare performance with the previous works the latest system models in terms of the datasets (Pin Face dataset). Based on the accuracy and the methods, statistical analysis was performed. Table 2 displays the performance of our system model and the latest system models in other studies. The models in table 2 used the face dataset in [20].

Ref.	**Accuracy %**
[10]	97.67%
[21]	94.8%
[22]	96.8 %
[23]	96.04%
[24]	85.5%
Proposed model	99%

Table 2 – Comparative performance of our system with recent models for face recognition.

Test the validity and effectiveness of the proposed model, it is tested with two different data sets. Table 3 illustrates the comparative result of the test of the proposed model for the detection of the disguised and makeup face [30] and the X-ray image of SARSCOVID19 [2]

Ref.	Dataset name	Accuracy	Accuracy of the proposed model
[2]	X-ray image	97%	98%
[33]	Disguised and makeup face	86%	95%

Table 3 – The comparative performance of our system and recent models for others dataset.

To sum up, of the above results the proposed model gets a good result and could be an alternative model for image recognition and retrieval.

5. Conclusion

The objective of this study is to develop a face recognition system. For this study, we used the Pins Face dataset published on Kaggle. The images in this dataset cover wide variations in pose, background clutter, lighting, age, facial expressions, and different people and are supported by many face images. It also has a reasonable range of accessories, such as glasses, hats, sunglasses, etc. This paper proposes an approach combining a deep learning model for feature extraction with machine learning algorithms for classification. In feature extraction, we pre-trained VGGFace2 with ResNet-50 model weights. Then, we applied the well-known classification algorithms to the feature extraction results to obtain the best result in each case and compared them based on accuracy. The result showed that VGGFace2 achieved higher accuracy with MLP and gave the best results in precision. In future studies, other machine classifiers can be used, and each of them could be combined to create a more sophisticated system. They should be able to detect with greater accuracy.

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