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Face Recognition using Deep Learning and TensorFlow framework

Rozpoznawanie twarzy przy użyciu głębokiego uczenia i frameworka TensorFlow

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Abstract
The detection and recognition of human faces, crucial for a wide range of applications, has made progress thanks to precise machine learning techniques. But the complexity can be daunting for newcomers. Our project focuses on building a Python-based framework for face recognition, with the aim of democratising access and fostering innovation. Harnessing the power of TensorFlow and Python, we painstakingly refined a CNN model using AT&T dataset. The results were striking, a remarkable in accuracy. With the strategic addition of layers, the accuracy of our model increased. While recognising the crucial role of accuracy, the importance of deployment time can't be overlooked. Our discussions also highlight the interplay between accuracy, operational efficiency and resource allocation.

Keywords: Face Recognition; Face Detection; CNN; TensorFlow

Streszczenie
Wykrywanie i rozpoznawanie ludzkich twarzy, kluczowe dla szerokiego zakresu zastosowań, poczyniło postępy dzięki precyzyjnym technikom uczenia maszynowego. Jednak ich złożoność może być zniechęcająca dla nowicjuszy. Nasz projekt koncentruje się na budowie platformy opartej na języku Python do rozpoznawania twarzy. Wykorzystując TensorFlow i Pythona, starannie dopracowaliśmy model CNN przy użyciu zbioru danych AT&T. Wyniki były uderzające, z niezwykłą dokładnością. Dzięki strategicznemu dodawaniu warstw, dokładność naszego modelu wzrosła. Nasze dyskusje podkreślają również wzajemne korelacje pomiędzy dokładnością, wydajnością operacyjną i alokacją zasobów.

Słowa kluczowe: rozpoznawanie twarzy; wykrywanie twarzy; CNN; TensorFlow

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1. Introduction

Facial recognition technology, which relies on the ability to distinguish individuals based on their facial features, plays a central role in security and law enforcement [1-5]. Despite its effectiveness, this technology faces a number of multifaceted challenges [9,10]. Concerns about invasion of privacy, algorithmic bias and security vulnerabilities underscore the urgent need for reliable deployment [11,12].

The ethical and competent use of facial recognition requires a comprehensive approach to ensure not only accuracy, but also adherence to quality standards that encompass functional meaning, reliability, performance, security and feasibility. This article embarks on a journey towards these goals and provides valuable insights into the field of facial recognition refinement, enriched by the capabilities of artificial intelligence and deep learning.

This article is organized as follows: Segment 2 digs into the scene of facial recognition, featuring its advantages for security and framing existing techniques. Area 3 presents our proposed technique, covering information assortment, pre-handling, extraction and the advancement of our FaceDetect framework. Sections 4 to 6 dig into the center of our examination, clarifying fundamental layers, introducing the engineering of our proposed CNN model, and thoroughly assessing its presentation. At long last, Segment 7 epitomizes our excursion, summing up our discoveries and preparing for future advances in facial recognition innovation.

2. State of the art

2.1. Benefits of facial recognition for security and use

Without a doubt, facial recognition innovation offers a few benefits in security and access control frameworks [7,13]. Its exactness in recognizing people in light of remarkable facial highlights makes it a solid and secure option in contrast to customary distinguishing proof techniques. The innovation likewise increments effectiveness by rapidly checking and recognizing people progressively [14-16], particularly in high-traffic regions like air terminals, arenas or transportation center points. By recognizing expected dangers, facial recognition innovation can further develop security and diminish the gamble of damage to individuals and property [17,18].

Facial recognition innovation can likewise assist with diminishing the expenses related with security and access control frameworks [12]. Customary distinguishing proof techniques, like actual identifications or passwords, are defenseless against misfortune or burglary and require incessant substitution and refreshing. Be that as it may, facial recognition innovation dispenses with these expenses by utilizing an individual's novel facial highlights to recognize them.

Generally, facial recognition innovation offers a few advantages in security and access control frameworks, further developing productivity, security and wellbeing while at the same time lessening costs.

2.2. Existing face recognition methods

An assortment of face recognition procedures are accessible, traversing traditional supervised and automated methods, as well as those utilizing the capacities of deep learning techniques.

2.2.1.Traditional methods

In face recognition, feature (descriptor) extraction plays a very important role in overall system performance. In the literature, two feature extraction environments exist: local features describing the dynamics of an image area, and global features entered by the attributes of the entire image.

2.2.2.Local features

Local descriptors, rooted in local features, focus on characterizing specific image regions [49]. Each descriptor captures sectorial details, requiring integration with other descriptors to form a holistic image representation. Elements such as intensity, color, and texture are considered local descriptors. These methods often rely on prior knowledge of facial structural morphology, involving the identification or extraction of local facial features. Local techniques offer the advantage of effectively addressing changes in pose, lighting, and facial expression.

Local Binary Patterns (LBP): LBP stands as a facial recognition approach centered on extracting texture features by representing faces as binary pattern histograms [27]. Unlike a global approach, LBP accentuates local texture nuances within facial images [28]. By sidestepping certain information losses linked to gradients, LBPs also capture diverse local structures [29]. This method's versatility is showcased in evaluating facial recognition performance for low-quality images [45].

Gabor Wavelets: Gabor filters, renowned for frequency localization and orientation selectivity, hold significance in image processing [50]. In the context of facial feature extraction, Gabor filters offer the advantage of capturing information across various orientations and scales. Although computationally intensive, Gabor methods find widespread use in image analysis and head pose estimation.

Oriented Gradient Histograms (HoG): Oriented Gradient Histograms, introduced by Dalal and Triggs, describe local and object appearances based on gradient intensity distribution [51]. This method operates by dividing images into cells, calculating gradient direction histograms for each cell, and combining these histograms to form the HoG parameter. It maintains invariance for geometric and photometric transformations, rendering it suitable for individual detection.

Scale Invariant Feature Transform (SIFT): Lowe's SIFT descriptor [52] identifies, characterizes, and describes interest areas within images, facilitating subsequent recognition in different images. This descriptor's value-based representation enables efficient matching of points of interest.

Convolutional Neural Networks (CNNs): In facial recognition, CNNs are adept at extracting local features [30]. By applying convolutional filters, CNNs unveil contours, textures, and patterns, generating local feature representations [31]. These local details amalgamate to form a comprehensive global representation of facial images.

2.2.3.Global features

The core concept is to extract a set of attributes computed over the entire image. This approach aims to transform the initial vectorised input face image into a lower dimensional space. This projection is carefully designed to highlight crucial and discriminative features that are essential for distinguishing between individuals. Many of these techniques delve into face subspace analysis, recognising that the face class occupies a subspace within the input image space (facespace). By focusing only on the relevant features - essentially the facial aspects - the dimensionality of these images can be reduced.

Early efforts in face recognition focused mainly on global features implicitly extracted by subspace decomposition methods. In particular, Eigenfaces and Fisher Faces embody this by projecting the entire face into a linear subspace, thereby capturing the range of facial variations.

Eigenfaces: This technique uses Principal Component Analysis (PCA) to extract facial features and represent them as Eigenfaces [19-21]. Eigenfaces are mathematical vectors that symbolize common facial feature variations in a dataset. During recognition, an input image is compared to the Eigenfaces to find the closest matches, facilitating individual identification. Known for its efficiency, Eigenfaces adeptly handles lighting, expressions and pose variations. Its real-world applications include access control, security systems, and surveillance [22].

Fisherfaces: Fisherfaces relies on the extraction of facial features using Linear Discriminant Analysis (LDA) [23-25]. LDA identifies features with substantial inter-individual differences while minimising within-person variation. This method identifies the most distinctive facial features for accurate identification. Fisherfaces is gaining ground in scenarios with limited samples per individual, extending its application to law enforcement, access control and surveillance [22,26].

2.3. Deep learning-based methods

Deep learning, an artificial intelligence methodology, operates through intricate neural networks and excels in learning from voluminous datasets. With prowess in tackling intricate tasks like image recognition and prediction, deep learning offers a potent avenue. Within deep neural networks, multiple interconnected layers of neurons facilitate the acquisition of hierarchical data representations. Deep learning's capacity to automatically extract pertinent local features contributes to remarkable performance across diverse domains. Convolutional neural networks (CNNs), particularly, hold promise, often outperforming conventional machine learning techniques [55]. This research spotlights deep learning's potential in bolstering agriculture and plant health, as it continues to reshape computing and various industries, continually redefining the boundaries of machine learning [54].

Convolutional Neural Networks (CNN): For facial recognition, a deep neural network model leverages specialized architectures like CNNs. In this structure, interconnected layers of neurons decipher distinctive features from images to identify individuals [30-33].

Siamese Networks: Siamese networks feature in facial recognition to gauge facial similarities. Employing identical segments, these networks extract local features from pairs of facial images. By comparing extracted features using a similarity metric, Siamese networks ascertain distances between faces of the same or different individuals. Their robustness shines, transcending lighting, expression, or pose variations. Training on extensive facial image pairs enables them to discern discriminative features that set individuals apart [30,34-36].

Triplet Networks: Triplet networks extend recognition by assessing groups of three faces to determine pairs belonging to the same individual [30,37]. This advanced approach crafts more discriminating facial representations, projecting faces into a space where faces of the same person converge while those of different people diverge [56].

Selecting the most fitting method hinges on factors such as accuracy, speed, and computational resources, as each technique possesses its unique advantages and limitations.

2.4. Advantages and limitations of learning-based

Learning-based approaches, such as deep neural networks, have become increasingly popular for facial recognition due to their ability to automatically extract relevant features and learn discriminative representations. However, they also have certain advantages and limitations that should be considered .

2.4.1.Advantages

- High accuracy: Learning-based approaches have been shown to achieve state-of-the-art performance in facial recognition tasks, often outperforming traditional methods [30,31,38].
- Robustness to variation: Learning-based approaches can handle variations in lighting, pose, and facial expression, making them more robust and reliable in real-world scenarios [31,38].
- Adaptability: Learning-based approaches can be trained on large datasets, making them highly adaptable to different face recognition tasks and applications[31,38].

2.4.2.Limitations

- Data Requirements: Learning-based approaches require large amounts of labeled data for training, which can be time-consuming and expensive to obtain [39,40].
- Computational Resources: Learning-based approaches can be computationally intensive, requiring powerful hardware and significant training time [41].
- Vulnerability to Adversarial Attacks: Learning-based approaches are vulnerable to adversarial attacks, where malicious actors can intentionally manipulate or modify input images to deceive the system [42-44].

Overall, learning-based approaches have shown great promise in facial recognition, but their advantages and limitations should be carefully considered when selecting a method for a specific application.

3. Methodology

The primary goal of face recognition is to detect and identify faces of different sizes, shapes and orientations. Within the field of computer vision, challenges in face detection and recognition remain, including issues such as illumination variations, occlusions and object orientations. Existing research highlights that conventional approaches using traditional features in supervised and global feature extraction systems have the advantage of preserving the holistic information, including texture, colour, position, lighting and shape, which are all critical for distinguishing faces within a set. These methods often represent faces as high-dimensional vectors proportional to the original image size. By merging or concatenating pixel values, these vectors are projected into a novel, lower-dimensional space, optimising the variance of the data. In particular, a face image is transformed into a linear combination of eigenvectors, which underpins the k-nearest neighbour (KNN) classification method [57].

However, there are inherent challenges due to uncontrollable factors such as pose, facial expression, lighting and occlusion, which ultimately affect recognition accuracy and lead to suboptimal performance [57,58]. In response, the deep learning paradigm [59] has emerged as a compelling alternative. Influenced by this development, we adopt the deep learning methodology, specifically using a convolutional neural network (CNN) powered by TensorFlow [60-62], an open source deep learning framework. This CNN-driven solution significantly improves face recognition by providing a robust basis for face detection.

In this context, the use of convolutional neural networks within deep learning manifests as a potent tool for increasing accuracy and precision in face detection and recognition tasks. Our proposed solution introduces a breakthrough approach that enables developers to effortlessly detect facial features and identify faces in images. Our architecture is a testament to this, culminating in a set of features that streamline and enhance the process.

The overall goal of our application is to increase the effectiveness of facial recognition, in line with the principles embedded in our code. Through iterative improvements, our mission focuses on improving critical aspects such as time efficiency, accuracy and memory usage. Through a series of improvements, we aim to pave the way for seamless future deployments of the application. We aim to achieve unparalleled performance, ensuring fast and accurate face recognition while optimising memory resources.

3.1. Data collection

The process of data acquisition is of paramount importance in the development of a Convolutional Neural Network (CNN) model. In this endeavour, the choice of dataset has a profound impact on the training and evaluation results. In this respect, the AT&T dataset [63] proves to be a central resource. This dataset plays a central role in both training and evaluating the effectiveness of machine learning models.

The AT&T face dataset, which consists of a set of facial images from 40 different individuals, is a comprehensive repository. Each individual is encapsulated by a collection of ten different facial images, which add up to a cumulative total of 400 images. With dimensions of 92x112 pixels, these images adhere to a greyscale color scheme using 256 levels per pixel. This dataset serves as a cornerstone that allows us to refine the capabilities of our CNN model, paving the way for refined and effective face recognition capabilities.

3.2. Optimization of face recognition system

The Convolutional Neural Network (CNN) architecture used in this work is a specialised deep learning framework tailored for image recognition and computer vision applications, with a focus on face recognition. Comprising a sequence of distinct layers, the CNN systematically extracts complex features from input facial images, enabling nuanced discrimination between individuals. The process begins with a convolutional layer, which convolves learnable filters over the input image to reveal elementary features such as edges and textures. Subsequent max-pooling layers downsample the extracted features to improve translation invariance. The flattening layer is used to reshape the transformed data, making it suitable for processing by fully connected layers. These densely connected layers of the neural network skilfully merge the extracted features, progressively constructing higher-level abstractions. Ultimately, the network's output layer provides probabilities corresponding to the potential identities, effectively achieving face classification.

This comprehensive design, using the TensorFlow library in Python as the programming framework, facilitated the exploration and development of the CNN model. In addition, the AT&T dataset, consisting of facial images of 40 individuals, was instrumental in training and fine-tuning the CNN model, resulting in a robust and accurate face recognition system.

In our study, we experimented with various parameters, such as the quantity and nature of layers, as well as the number of epochs, in order to conduct a comprehensive performance evaluation. We assessed the performance using the AT&T dataset, as shown in this Table 1.

Table 1: A brief description of the datasets AT&T

	Class	Training	Testning	Dimension
AT&T	40	400	40	(112*92)

4. Essential layers to develop CNN

In my experiments, I began by constructing a fundamental CNN model that incorporated four essential layers: Conv2D, MaxPooling2D, Flatten, and Dense. This architecture is detailed in Table 2. Convolutional Neural Networks (CNNs) incorporate various filters or kernels, each equipped with trainable parameters. These filters convolve spatially over an input image, detecting features such as edges and shapes. The abundance of these filters effectively learns to capture spatial characteristics, driven by the weights acquired through backpropagation. Stacked filter layers further enable the identification of intricate spatial patterns, progressively transforming the image into a highly abstracted representation conducive to predictive tasks.

Table 2: Architecture of essential CNN model

Layers	Output Shape	Parameters
Conv2D	(110, 90, 32)	320
MaxPooling2D	(55, 45, 32)	0
Flatten	(79200)	0
Dense	40	3168040
Total parameters		3168360

The fondamental model architecture consists of quatre layers designed to process and extract complex features from the input data. Starting with a Conv2D layer. A MaxPooling2D layer then reduces the output dimensions. The Flatten layer then reshapes the data, allowing efficient data manipulation. Finally, the Dense layer with 40 output nodes or class, contributing to the complexity and ability of the model to learn and predict patterns in the data.

5. Architecture of proposed CNN

The proposed model in Table 3 introduces a number of improvements that contribute to its improved performance and efficiency. By introducing batch normalisation after each Conv2D layer, the model's ability to generalise and learn from the data is enhanced. This ensures that the network's intermediate outputs are normalised, mitigating potential problems associated with vanishing gradients and accelerating convergence. In addition, the inclusion of MaxPooling2D layers aids spatial reduction, allowing the model to focus on essential features and patterns while minimising computational load.

Taking into account the optimisation of the architecture, the number of parameters is significantly reduced compared to the original model. These design choices improve the model's ability to capture complex features while maintaining a more streamlined number of parameters. This translates into improved training speed and reduced risk of overfitting, ensuring the model's effectiveness and adaptability across different applications.

Table 3: Architecture of proposed CNN model

Layers	Output Shape	Parameters
Conv2D	(110,90, 32)	320
BatchNormalization	(110, 90, 32)	128
Max_pooling2D	(55, 45, 32)	0
Conv2D	(53, 43, 64)	18496
BatchNormalization	(53, 43, 64)	256
MaxPooling2D	(26, 21, 64)	0
Conv2D	(24, 19, 128)	73856
Flatten	(58368)	0
Dense	(40)	2334760
Total parameters		2427816

6. Evaluation of the performance of essential layers to develop CNN model

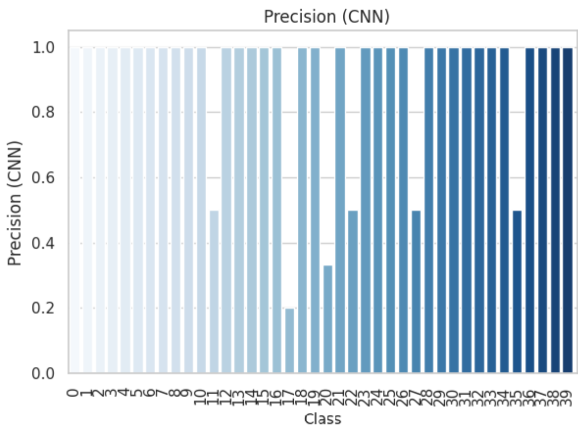

Figure 1: Precision Distribution Before Enhancement.

In Figure 1 shows the distribution of accuracy values for the different classes. The basic architecture of a CNN for facial recognition clearly shows that it is preferable to test several modifications before arriving at a high-performance, reliable architecture. The variation in recognition accuracy between the different classes is evident. Some classes show higher accuracy, while six classes achieve accurate recognition. This analysis provides an overview of the initial performance of the fundamental model, highlighting areas of strength and areas for improvement. In the following experiment in section 7 we try to improve the quality of the system in terms of functional relevance and performance indicators of a calculation.

Table 4: Global metrics essential layers to develop CNN model

Parameterization	Values
CNN Layers	4
Epochs	10
Accuracy	90.8%
Training time	21.26 (s)
Testing time	0.15 (s)
Total memory	6576 bytes

Table 4 present the underlying setup and the outcomes got for a fundamental design of the CNN model.The CNN model, made out of an information convolutional layer with 32 channels followed by a maximum pooling layer, accomplished a precision of 0.908 on the acknowledgment task. The preparation time was 21.27 seconds, while the testing time was 0.15 seconds, for a presentation concentrate on as far as execution time in time space. The memory usage of the model during execution was 48 bytes, and the memory usage for putting away the expectation probabilities was 6528 bytes for an exhibition concentrate on as far as memory space and assets consumed.

This description sums up the key execution measurements and asset use parts of your CNN model in a reasonable and succinct way.

7. Evaluation of the performance of the proposed model

We rolled out a few improvements to the design of our CNN model, which prompted a huge improvement in recognition execution. We expanded the intricacy of the model by adding additional layers. The design currently comprises of three successive convolutional layers, each followed by a clump normalization layer to upgrade stability and convergence during preparing. We likewise presented a new convolutional layer with 256 filters. To forestall overfitting, we incorporated a dropout layer with a pace of 0.5.

Table 5: Global metrics of the proposed model

Parameterization	Test 1 (Values)	Test 2 (Values)
CNN Layers	9	9
Epochs	10	20
Accuracy	85%	96.3%
Training time	204.49 (s)	203.13(s)
Testing time	0.61 (s)	0.82 (s)
Total memory	6576 bytes	6576 bytes

Table 5 shows the modifications be made to the basic model and the variation in parameters such as the number of layers, the number of epochs and the results. We extended the training duration to 20 epochs to allow for better convergence and feature learning. As a result of these improvements, our CNN model exhibited a noticeable boost in precision, achieving a value of 0.963. The training process took approximately 287.5

seconds, while the testing time was around 0.88 seconds.

In Figure 2 the chart showcases the change in precision distribution across classes after implementing model enhancements. The disparity among class-specific precision values has notably reduced. The refinement efforts, aimed at enhancing overall accuracy, have yielded a more balanced distribution. This analysis emphasizes the positive impact of strategic modifications on recognition accuracy across a range of facial features and expressions. The chart underscores how our adjustments have led to improved precision for a wider classes.

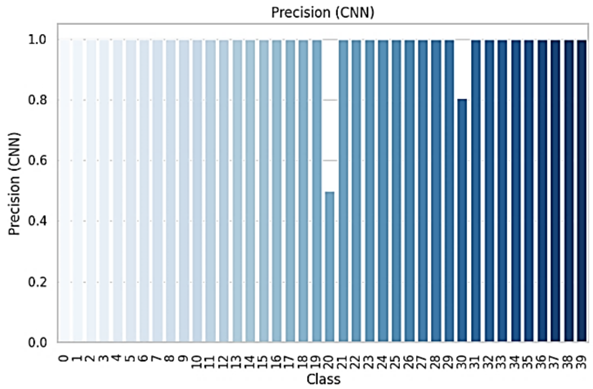

Figure 2: Precision Enhancement Impact.

Throughout execution, the model's memory usage remained consistent at 48 bytes. The memory used for storing prediction probabilities remained at 6528 bytes. The overall memory utilization during execution was unchanged at 6576 bytes.

8. Conclusions

Our journey to enhance the CNN model's architecture led us to substantial improvements in recognition accuracy, empowered by the combined forces of TensorFlow and Python. The essence of these enhancements is most vividly captured in the precision rates 0.90 initial and post-enhancements 0.96 signifying our model's prowess in facial recognition accurately.

While acknowledging the importance of recognition precision, it's equally vital to consider execution efficiency. The discussions around training time and memory space shed light on the practical implications of deploying such models. With the CNN model dynamic architecture of facial recognition constantly evolving, our findings serve as a valuable compass, guiding the optimization of recognition accuracy and resource utilization alike.

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