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ADAPTIVE FILTER FOR REDUCING FALSE POSITIVES IN FACE RECOGNITION FROM IMAGE AND VIDEO INPUTS

G.K.SHASHANKA
Research Scholar (VTU Belagavi), Department of Business Administration, St Joseph Engineering College, Mangaluru, Karnataka, India.

ANJALI GANESH*
Department of Business Administration, St Joseph Engineering College, Mangaluru, Karnataka, India.
*Corresponding Author Email: anjalig@sjec.ac.in

SHRISHA H S
Department of Computer Science & Engineering, St Joseph Engineering College, Mangaluru, India.

Abstract

In recent years, significant progress has been made in Face Recognition (FR) systems, finding diverse applications such as security, authentication, surveillance, and user convenience. Despite these advancements, a persistent challenge in FR systems is the occurrence of false positives, where individuals are mistakenly identified as matches. This issue can lead to security breaches, privacy concerns, and user dissatisfaction. Researchers are actively developing deep-learning-based algorithms to enhance FR systems by addressing false positive (FP) rates. This paper introduces an innovative approach to tackle false positives in real-time face recognition systems that operate on image streams using a filtering method. Instead of treating every identification as a match, our method dynamically filters false positive results using a larger database containing recent and necessary face images. This filtering technique significantly decreases the number of false positive cases, resulting in a more accurate and reliable face recognition system. The experimental results presented in this paper illustrate the effectiveness of our approach in reducing false positives across various challenging scenarios. By adapting to the specific context in which face recognition is applied, our method achieves a noteworthy reduction in false positives while maintaining a high level of accuracy and efficiency. In summary, mitigating false positives in face recognition stands as a crucial stride in unlocking the complete potential of this technology, simultaneously addressing apprehensions regarding its potential misuse. Our innovative false positive filtering approach presents a promising resolution to this challenge, laying the foundation for the development of more secure and reliable face recognition systems across diverse domains.

Keywords: *Face Recognition, Deep Learning, False Positive, Face Analytics, Face Dataset.*

1. INTRODUCTION

The rapid advancement of artificial intelligence has profoundly transformed various fields, with face recognition (FR) technology emerging as a focal point of innovative applications [23], [4]. As society becomes increasingly reliant on automated systems for security and identification purposes, the urgency to refine these technologies has never been more critical. In FR systems, the accuracy of identity verification is paramount; however, the prevalence of false positives (FP) poses significant challenges [23]. These errors not only undermine the reliability of these systems but can also lead to severe implications such as wrongful accusations or unauthorized access. To address these concerns, this research focuses on developing a robust false positive filter designed to enhance the accuracy and reliability of face recognition systems. By analyzing existing methodologies and introducing a novel

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filtering approach, this study aims to significantly reduce the incidence of false positives while maintaining operational efficiency.

FR systems, akin to other biometric technologies, are prone to false positives, where someone is incorrectly identified as a match despite being different individuals. Various factors contribute to this issue:

- Input Data Quality: Low-quality images, poor lighting, and pose variations lead to inaccuracies [3], [4], [24].
- Database Size/Diversity: Smaller, less diverse databases increase false positives [13], [26].
- Algorithm Accuracy: Some algorithms may be more prone to errors [26].
- Environmental Conditions: Changes in lighting or camera angles affect accuracy [4].
- Individual Similarity: Similar facial features make differentiation challenging [11], [20].
- Threshold Settings: Adjusting match thresholds affects false positives/negatives [20].

To mitigate false positives, system developers/operators can:

- Utilize high-quality, diverse training data to improve the algorithm's accuracy and generalization [4], [13].
- Regularly update and fine-tune algorithms to improve performance and reduce errors [1], [20]
- Optimize threshold settings per use case on the specific use case and requirements of the system [20].
- Ensure proper lighting and camera setup to capture high-quality images for matching [4], [10].
- Implement multi-factor authentication approach to complement face recognition, such as combining it with a password or a physical token [25].

In this paper, we propose an innovative FP filter that can be implemented with any FR algorithm to reduce the FP rate in FR. The filter operates by reapplying the face recognition (FR) process using a larger training database, automatically generated based on recently captured faces in an ongoing manner. It effectively eliminates or rectifies false positive identifications made during the initial FR stage.

Typically, the filter is applied post-FR, as the database involved is larger, requiring additional time for the filtering process. In scenarios like live feed FR, where the entire process must be completed within seconds, applying the filter after FR is more practical than integrating it into the FR process. This background filter process doesn't introduce any latency to FR but significantly reduces the false positive rate in the final report, fulfilling the primary objective.

This approach holds promise for enhancing the quality of FR systems, particularly for handling low-quality images and live feeds on machines with Personal Computer configurations.

Recognizing the evolving nature of face recognition technology, it's crucial to acknowledge that false positives represent a trade-off between convenience and security. Achieving the right balance between accuracy and usability is vital for effective deployment in real-world scenarios [26]. Moreover, ethical and privacy considerations are paramount to prevent potential misuse or harm when employing face recognition technology.

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2. LITERATURE REVIEW

Many related studies have been done in the literature on the accuracy and quality of face recognition systems. A modified Adaboost algorithm [1] for face detection was introduced to reduce false-positive detection rates by assigning higher weights to weak classifiers with the best positive classifications. The system considers the total error of weak classifiers and classification probability. The probability is determined by computing both positive and negative classification errors for each weak classifier. Experimental findings demonstrate a nearly fourfold reduction in false positives compared to the original Adaboost, while maintaining comparable face detection rates.

Ignorance in deep-learning-based face recognition [2] focuses on addressing the first concern by exploring the technique of "blinding" models to sensitive features like gender or race. However, the study reveals that reducing the model's awareness of these features does not necessarily correlate with a decrease in accuracy, challenging the notion that blinding is an effective de-biasing method. A Profile to Frontal Revise Mapping (PTFRM) module [3] was introduced which aimed at revising arbitrary poses on the feature level. This module transforms multi-pose features into an approximate frontal representation, enhancing the recognition capabilities of existing models. Evaluation on benchmark datasets, including Labeled Faces in the Wild (LFW), Celebrities in Frontal Profile (CFP), and IARPA Janus Benchmark A (IJB-A), demonstrates the method's effectiveness, showcasing good performance in unconstrained face validation scenarios. Authors provide a comprehensive examination of various challenges [4] in face recognition systems, exploring existing techniques proposed in the literature to address these issues. Additionally, analyzes of major face datasets incorporating diverse facial constraints to mimic real-life scenarios, outlining associated shortcomings are carried out. A novel end-to-end deep learning model [5] was proposed that simultaneously addresses facial expression recognition, face image synthesis, and face alignment. This model utilizes expression and geometry codes, along with generated data, to disentangle global and local identity representations. The disentanglement enables the automatic generation of facial images with diverse expressions under arbitrary geometry codes. The model also leverages joint learning to enhance the performance of each task, with facial expression recognition contributing to face synthesis and alignment.

An Attention Augmented Network, AAN-Face [6] was introduced to handle occlusions and pose variations. It incorporates an attention-erasing (AE) scheme that randomly removes units in attention maps to prepare models for occlusions and pose variations. Additionally, an attention center loss (ACL) is introduced to assign a center to each attention map, emphasizing discriminative facial regions and suppressing useless or noisy ones. The proposed Coupled Attribute Learning for Heterogeneous Face Recognition (CAL-HFR) [7] approach enables the integration of attribute discriminative information without the need for manually labeled attributes, making it suitable for large-scale matching. The approach has ability to leverage discriminative attribute information, which is deemed crucial for Heterogeneous Face Recognition (HFR). A college attendance monitoring problem [8] is addressed by considering four directions to the problem: the accuracy rate of the face recognition system in the actual check-in, the stability of the face recognition attendance system with real-time video processing, the truancy rate of the face recognition attendance system with real-time video processing and the interface settings of the face recognition attendance system using real-time video processing. Experimental data shows that the accuracy rate of the video face recognition system is up to 82%. Compared with the traditional check-in method, the face recognition attendance system can be reduced by about 60%. The authors present a novel face shape-guided deep feature alignment framework [9] for Face Recognition (FR) to enhance robustness against face misalignment. Utilizing a face shape prior, such as facial keypoints, they train a deep network with alignment processes, including pixel and feature alignments, between well-aligned and misaligned face images. The pixel

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alignment process involves decoding aggregated features from a face image and face shape prior, introducing an auxiliary task of reconstructing well-aligned face images. The feature alignment process connects the aggregated features to the face feature extraction network, training robust face features against misalignment. Importantly, although face shape estimation is necessary during training, the additional face alignment process commonly used in conventional FR pipelines is not required during testing. A novel identity-conscious face super-resolution network [10] was introduced which aimed at restoring identity details of low-resolution (LR) faces. To efficiently capture identity-conscious characteristics, identity features are explicitly decomposed into two independent components: the magnitude and angle of features, which map identity attributes onto a hypersphere space. Two models: DepthNet and segmentation-guided RGB-D face recognition model [11] were introduced. Incorporate cross-modal focal loss, semantic alignment loss, and feature disentanglement loss to enhance face identity representation. Age Invariant Model (AIM) [12] with three key advancements is introduced. Firstly, it integrates cross-age face synthesis and recognition, mutually enhancing performance. Secondly, it achieves continuous face aging/rejuvenation with photorealism and identity preservation, without paired data or precise age labels. Thirdly, AIM employs novel end-to-end training strategies, generating potent age-invariant face representations. Additionally, a large-scale CAFR benchmark dataset is developed. Extensive experiments demonstrate AIM's superiority over existing methods, with strong generalization on unconstrained face recognition datasets. The challenge of NIR-VIS masked face recognition [13] can be tackled by addressing training data and methods. It introduces a novel heterogeneous training approach to enhance mutual information between face representations from two domains using semi-siamese networks. Additionally, a 3D face reconstruction method is employed to synthesize masked faces from existing NIR images. The solution offers domain-invariant face representations resilient to mask occlusion. A novel heterogeneous training approach [14] is introduced to enhance mutual information between face representations from two domains using semi-siamese networks. Also, a 3D face reconstruction method is used to synthesize masked faces from existing NIR images. Through these techniques, the solution offers domain-invariant face representations resilient to mask occlusion as in [13]. To address the sensitivity to quality and quantity of training data, a Face Augmentation Generative Adversarial Network (FA-GA) [15] was introduced, which reduces the impact of imbalanced deformation attribute distributions. This approach employs a hierarchical disentanglement module to separate attributes from identity representations, and Graph Convolutional Networks (GCNs) to recover geometric information and preserve identities in face data augmentation. A novel million-scale recognition benchmark, WebFace260M [16], comprises uncurated 4M identities and 260M faces, and cleaned WebFace42M with 2M identities and 42M faces, alongside a meticulously designed time-constrained evaluation protocol. Cleaning automatically using Self-Training (CAST) pipeline is used to purify WebFace260M efficiently. Our benchmark bridges the academia-industry data gap and the technique facilitates practical deployments with the Face Recognition under Inference Time conStraints (FRUITS) protocol for a comprehensive evaluation on standard, masked, and unbiased settings. With WebFace42M, technique achieves a 40% reduction in failure rates on IJB-C and rank 3rd in NIST-FRVT. MTLFace [17] uses a unified framework addressing age-invariant face recognition (AIFR) and face age synthesis (FAS). By decomposing mixed face features into identity- and age-related components through attention-based feature decomposition, it achieves improved AIFR and artifact-free FAS. Leveraging high-quality synthesized faces, MTLFace employs selective fine-tuning to enhance AIFR.

Considering all the above studies, it is observed that the FP rate can be further decreased. Also, a generic and simpler way of implementation of filter can be done. In our work a unique algorithm for FP filter has been proposed which is a generic solution for both video and images. Also, near to 100% accuracy can be achieved. It can be integrated with any FR algorithms.

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3. METHODOLOGY

3.1 System model

The model proposed in our work introduces a false positive (FP) filter for FR, aiming to minimize or eliminate false positives in the final report. Illustrated in Figure 1, the revised flow for FR report generation with the FP filter is outlined as follows:

- Conduct FR on live camera feed (or saved images/videos) using trained face images.
- Filter recognized images for false positive results using a larger database containing recent database images.
- Incorporate recent images from the filtered data into the database used by the filter, ensuring a continuous update process.
- Generate the required report from the filtered data, which contains fewer or no false positives.

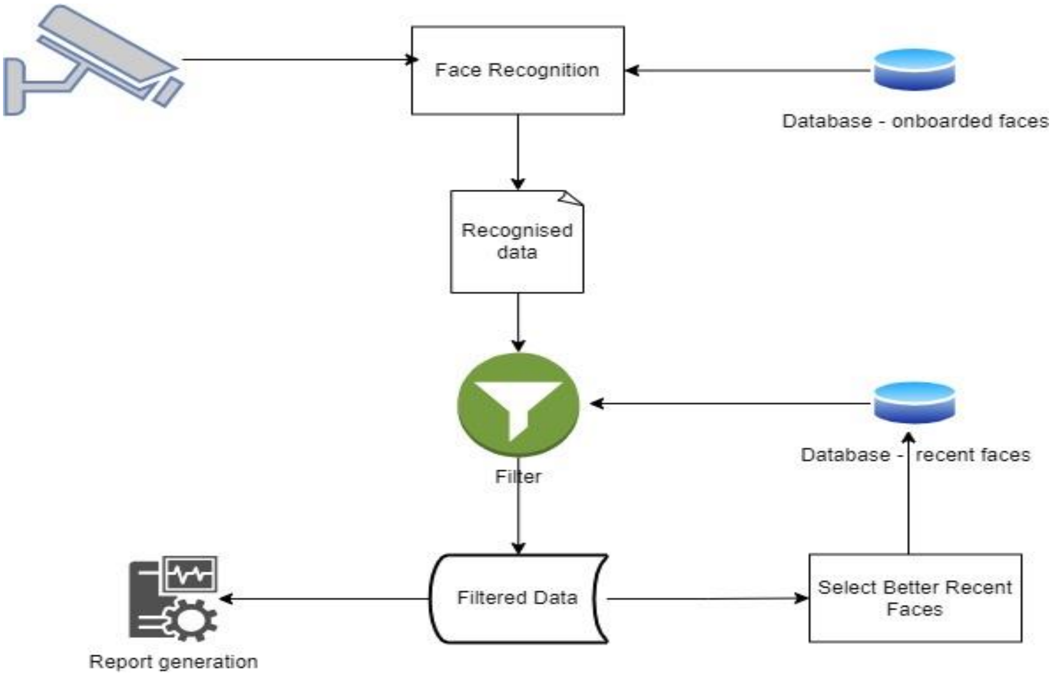

Figure 1: Block diagram of the FR system indicating the accomplished filtration process

3.2. Algorithm

Step 1: Create a training database with at least 5 face images for each person

Step 2: Select new test images set for verification. Test images are new face images and should not be part of training database

Step 3: Execute FR functionality against the trained database using a test image from the set of test images

Step 4: Apply threshold as per the FR algorithm used in Step 3

Step 5: If the FR score is within threshold limit go to step 6 otherwise go to Step 3 and repeat the procedure for next test image

Step 6: Check how many times the test image matched to different people irrespective of threshold for the result in Step 3

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Step 7: If the test image matches more times to another person other than to the one matched within threshold in Step 3, consider it as False Positive case and correct the FR match to the person having more number of matches to the image.

Step 8: Go to step 3 for next test image if available else go to Step 9

Step 9: Stop

4. EXPERIMENTAL STUDY

4.1 System Configuration

In our experiment we used the following system configuration to check how the filter reduces FP rate. We have chosen entry level hardware configuration so that considerable amount of FPs are available for the experiment.

Table 1: System configuration and the corresponding software environment

Sl. No.	Hardware configuration	Software environment
1	Intel core i3 processor, 6th generation	Ubuntu Operating System
2	8GB RAM (Random Access Memory)	Python programming language
3	256GB SSD (Solid State Drive)	Deepface FR python package [22]

4.2 Dataset

Pins Face Recognition dataset [18] has been used in the experiment. The dataset sample is shown in Fig. 4. The specifications of the dataset are as follows.

Total number of images: 17534

Total number of persons/classes: 105

Average number of images per person: 167

Number of images used for Testing: 4410

Number of images used for Training: 13124

4.3 Implementation

We have tested DeepFace, Vgg-Face and Facenet512 FR algorithms using above dataset and system configuration mentioned in Table 1 in two iterations for each algorithm.

Iteration 1: Direct FR algorithm without the filter program

Iteration 2: FR Algorithm with the filter program

Confusion matrix [19] has been drawn for each experiment outcome and is as shown in Fig. 2. Along with True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) counts the confusion matrix boxes show accuracy percentage and Misclassification Rate percentage.

The statistical measure have been calculated as per the below list of formulae and expressions.

Precision=TP/(TP + FP)

Recall (Sensitivity)=TP/(TP + FN)

Accuracy = (TP + TN) / (TP + TN + FP + FN)

F1 Score=2*Precision*Recall/Precision + Recall

Macro-F1 is the average of F1 Scores

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Weighted-F1 is given by weighted-averaged of F1 Scores

Misclassification Rate=number of incorrect predictions/ total number of predictions

TARGET / OUTPUT	Positive	Negative	SUM
Positive	1899 43.06%	111 2.52%	2010 94.48% 5.52%
Negative	0 0.00%	2400 54.42%	2400 100.00% 0.00%
SUM	1899 100.00% 0.00%	2511 95.58% 4.42%	4299 / 4410 97.48% 2.52%

(a) DeepFace without filter

TARGET / OUTPUT	Positive	Negative	SUM
Positive	1712 38.82%	298 6.76%	2010 85.17% 14.83%
Negative	0 0.00%	2400 54.42%	2400 100.00% 0.00%
SUM	1712 100.00% 0.00%	2698 88.95% 11.05%	4112 / 4410 93.24% 6.76%

(b) DeepFace with filter

TARGET / OUTPUT	Positive	Negative	SUM
Positive	1899 43.06%	111 2.52%	2010 94.48% 5.52%
Negative	0 0.00%	2400 54.42%	2400 100.00% 0.00%
SUM	1899 100.00% 0.00%	2511 95.58% 4.42%	4299 / 4410 97.48% 2.52%

(c) Vgg-Face without filter

TARGET / OUTPUT	Positive	Negative	SUM
Positive	1969 44.65%	41 0.93%	2010 97.96% 2.04%
Negative	0 0.00%	2400 54.42%	2400 100.00% 0.00%
SUM	1969 100.00% 0.00%	2441 98.32% 1.68%	4369 / 4410 99.07% 0.93%

(d) Vgg-Face with filter

TARGET / OUTPUT	Positive	Negative	SUM
Positive	1899 43.06%	111 2.52%	2010 94.48% 5.52%
Negative	0 0.00%	2400 54.42%	2400 100.00% 0.00%
SUM	1899 100.00% 0.00%	2511 95.58% 4.42%	4299 / 4410 97.48% 2.52%

(e) Facenet512 without filter

TARGET / OUTPUT	Positive	Negative	SUM
Positive	1990 45.12%	20 0.45%	2010 99.00% 1.00%
Negative	0 0.00%	2400 54.42%	2400 100.00% 0.00%
SUM	1990 100.00% 0.00%	2420 99.17% 0.83%	4390 / 4410 99.55% 0.45%

(f) Facenet512 with filter

Figure 2: Confusion matrix for the algorithm with and without filter using DeepFace,Vgg-Face and FaceNet512

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4.4 Experimental Results

After analyzing the confusion matrices mentioned in Fig. 2, we have noted the improvement in accuracy due to the FP filter for different FR algorithms. Table 2 and Fig 3 below provide the necessary details.

Table 2: Comparison of the algorithms for accuracy compared to Initial FR done directly without the filter

Sl No	Algorithm	Accuracy with filter	Improvement in accuracy (%)
1	DeepFace	0.9324	-4.22
2	VGG-Face	0.9907	+1.61
3	Facenet512	0.9955	+2.09

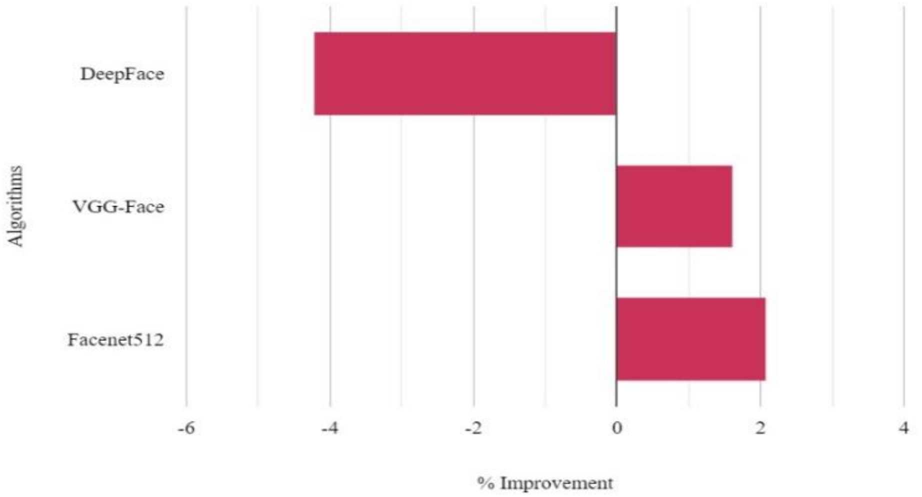

Figure 3: Bar chart [21] representing the percentage of accuracy improvements

Figure 4: Dataset sample [18]

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5. CONCLUSION AND DISCUSSIONS

From Table 2 and Fig. 3 we can see that accuracy of VGG-Face and Facenet512 improved after filter whereas accuracy of Deepface reduced. We have also done experiments using MTCNN and Facenet algorithms. They have also improved in similar lines as in VGG-Face and Facenet512. Hence it is not considered in the analysis. Thus, we can conclude that the Filter improves the FR false positives cases considerably. Also we can observe that Facenet512 accuracy is 99.55% after applying the FR Filter that is well accepted for systems like Face Recognition based attendance system, Face Analytics etc. The filter can be integrated with the concept of scene change indicator [20] in live streaming videos. This filter can work for images, videos and live streaming.

The algorithm mentioned in this study concentrates a new approach of building FP filter for FR which can be incorporated with any FR algorithms available. We have tested it with existing high efficient FR algorithms like VGG-Face, Facenet512, MTCNN, Facenet. The filter has reduced FP rate considerably as mentioned in the results section. In addition to adaptability to any FR algorithms, it can be applied to any type of face dataset such as images, video, live streaming. The study also chose low quality images in minimal hardware configuration to ensure that it can be used in single board computers. Hence, it becomes more generic and can be easily incorporated in any low end or high end configuration systems, with low computation cost.

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