IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A HYBRID CLASSIFIER FOR FAST AND EFFICIANT FACE RECOGNITION USING LBP ALGORITHMS

[1]Abhishek Kumar Agrahari, [2]Priya Chauhan, [3]Vikas Gupta

[1]Assistant Professor, Department of Computer Science and Engineering. Invertis University, Bareilly, Uttar Pradesh, 243123 India,

[2]Assistant Professor, Department of Computer Science and Engineering. Invertis University, Bareilly, Uttar Pradesh, 243123 India,

[3]Student of Bhagwant Pandey Mahavidyalaya Bodarwar, Uttar Pradesh, 274149, India.

Abstract: This paper introduces a hybrid classifier designed to achieve rapid and efficient face recognition by leveraging Local Binary Pattern (LBP) algorithms. Our proposed approach capitalizes on the strengths of LBP-based feature extraction methods while incorporating different classifiers, such as Support Vector Machine (SVM) and Random Forest (RF), to enhance recognition performance.

The process involves extracting LBP features from the input face image, which are then utilized as input to the classifiers. By combining these elements, our hybrid classifier achieves high accuracy in face recognition while significantly reducing computational complexity and processing time compared to traditional LBP-based methods.

To validate the effectiveness of our approach, we conducted experiments on publicly available face recognition datasets. The experimental results confirm the superiority of our hybrid classifier, making it a suitable choice for real-time face recognition applications.

Index Terms **- Face Recognition, High accuracy using hybrid classifier SVM+RF, Local binary patterns (LBPs) for Feature Extraction.**

I. INTRODUCTION

Face recognition is a prominent area of study with diverse applications in security, surveillance, and biometrics. There is an increasing demand for real-time face recognition, necessitating swift and accurate algorithms. Local Binary Pattern (LBP) is a widely utilized texture descriptor that has shown promise in face recognition tasks. Nevertheless, traditional LBP-based methods have limitations concerning accuracy and processing time.

To overcome these limitations, this research proposes a hybrid classifier for rapid and efficient face recognition, employing Local Binary Pattern (LBP) algorithms. The proposed approach combines the strengths of LBP-based feature extraction methods with various classifiers like Support Vector Machine (SVM) and Random Forest (RF) to enhance recognition performance. The LBP features extracted from the input face image are utilized as inputs to the classifiers.

The primary objective of the proposed hybrid classifier is to enhance face recognition accuracy while reducing computational complexity and processing time compared to conventional LBP-based methods. The effectiveness of this approach is demonstrated through experimental results using publicly available face recognition datasets.

The subsequent sections of the research are organized as follows: Section 2 provides a concise overview of related work in the field. Section 3 presents a comprehensive description of the proposed hybrid classifier. In Section 4, the research showcases the experimental results and provides a thorough performance analysis. Finally, Section 5 presents the conclusions drawn from the study and outlines potential directions for future research.

II. BRIEF OVERVIEW OF RELATED WORK

A common texture descriptor in computer vision applications, such as face recognition, is the local binary pattern (LBP). Numerous academics have suggested various LBP-based methods for recognizing faces, including the LBP histogram, LBP-based local features, and LBP-TOP. However, the accuracy and processing time of conventional LBP-based algorithms are constrained.

Researchers have suggested numerous improvements to the conventional LBP-based approaches to deal with these limitations. To increase the accuracy of recognition, Liu et al. [1] introduced an adaptive LBP method that modifies the extraction threshold for LBP features. To increase the reliability of face recognition, Zhang et al. [2] suggested a multi-scale LBP technique that extracts LBP characteristics at several scales.

In addition, researchers have also investigated the use of different classifiers with LBP-based features for face recognition. For instance, Wang et al [3]. used a combination of LBP and SVM for face recognition, while Bhattacharyya et al [4]. used LBP and

Some researchers have also explored the use of ensemble classifiers such as Random Forest (RF) with LBP-based features for face recognition.
Despite these efforts, there is still a need for fast and efficient face recognition algorithms that can maintain high accuracy. In this paper, we propose a novel hybrid classifier that combines LBP-based feature extraction with different classifiers to achieve high accuracy in face recognition while reducing processing time.

III. OVERVIEW OF FACE RECOGNITION AND RELEVANT ALGORITHMS

Facial recognition research has a long history that dates back to the 1960s. The earliest work in this area focused on developing algorithms for detecting and recognizing facial features, such as the eyes, nose, and mouth, in still images. In the 1990s, researchers began to explore the use of machine learning algorithms, such as neural networks and support vector machines, for face recognition. In the early 2000s, the availability of large-scale face databases, such as the FERET database and the CMU Multi-PIE database, enabled researchers to develop more sophisticated face recognition algorithms. Many of these algorithms were based on features extracted from facial images, such as Eigenfaces, Fisherfaces, and Local Binary Patterns (LBP).

Overall, during the past few decades, the field of facial recognition has advanced significantly, and research and development in this area are still very busy.

3.1 The fundamentals of facial recognition

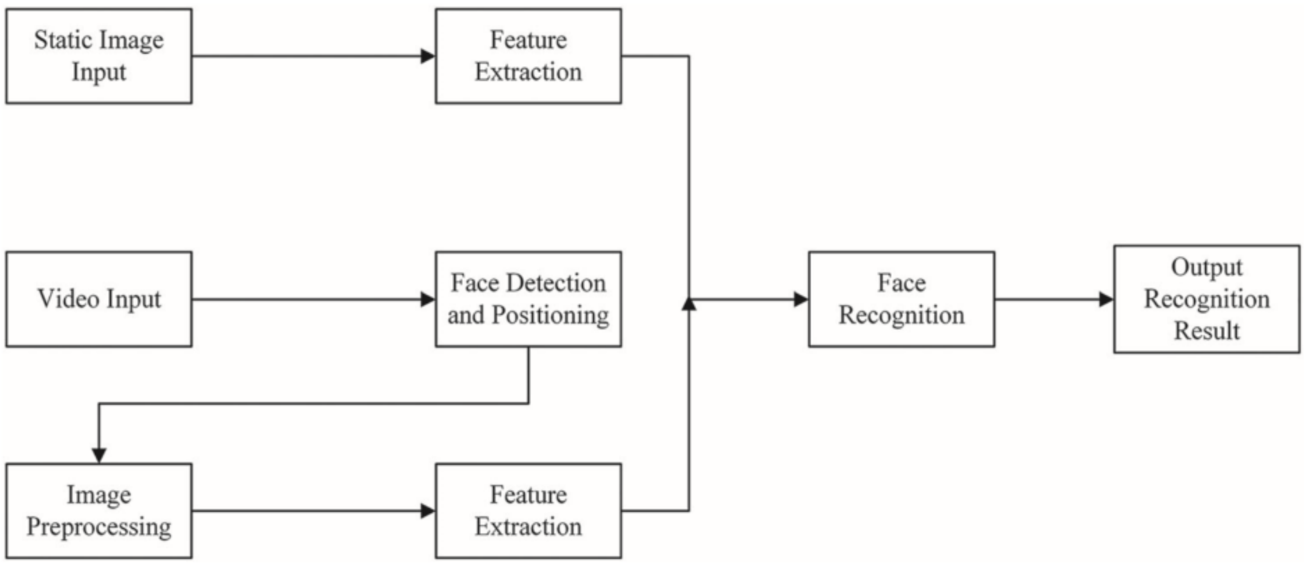

Figure 1: The fundamentals of facial recognition

Facial recognition involves four phases, as shown in Figure 1: image gathering, image preparation, feature extraction, and recognition.
In the image gathering and inspection process, facial photographs are collected, and relevant portions of the images are retrieved and located, focusing on facial features like the mouth, nose, eyes, and face shape. The Honda/UCSD video database will be used for this research.

Image preparation aims to eliminate disasters, remove unnecessary elements, and enhance image quality. This simplifies the facial recognition process and reduces the impact of misunderstandings in photo sets.
Feature extraction is crucial in reducing computation costs. It involves obtaining useful information from the collected facial data to represent each face effectively. Face recognition technology uses a photo set that contains numerous photographs of a single individual, each with its own attributes.

During recognition, the targeted page is compared to the dormant B attribute, and the database's attributes labeled B are compared to the B attribute. By comparing and recognizing photographs, similarities in facial features are identified. The distance between two photo sets is related to the degree of matching for facial recognition using a photo set.

Facial recognition techniques require sufficient training data for acceptable accuracy. The present available page sample data may have a low average number of pages per user, making it challenging to train deep learning network models without enough data. The effectiveness of feature extraction techniques and related algorithms significantly influences facial recognition accuracy, making databases crucial for training an optimum network model.
The four procedures mentioned above are necessary and crucial for facial identification when employing the examined photo sets, as shown in Figure 2. The image set poses additional challenges for modeling and recognition accuracy.

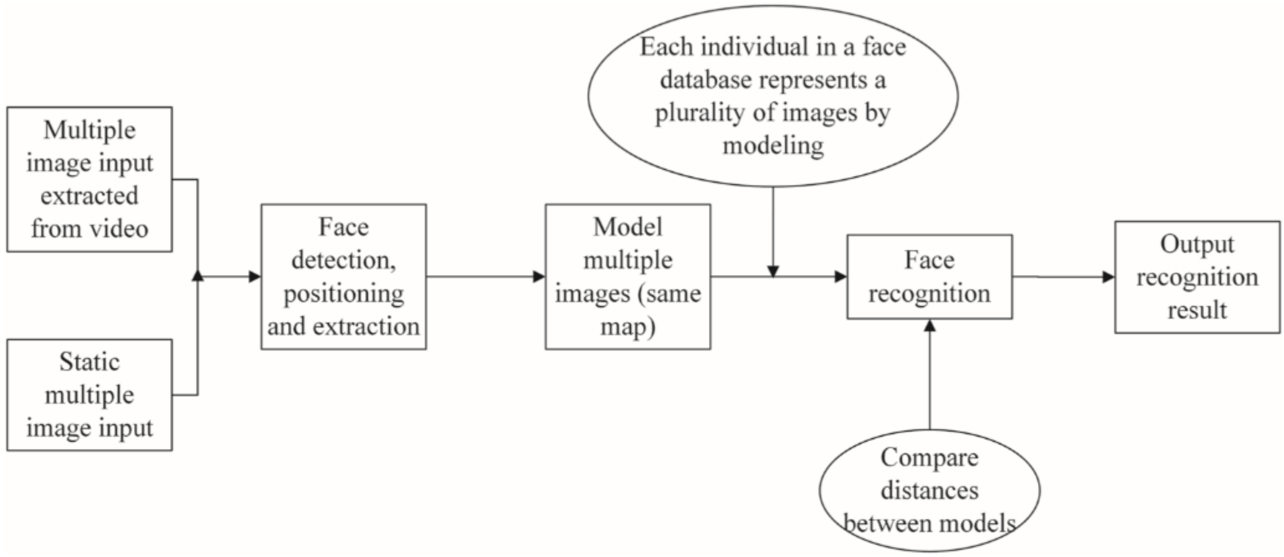

Figure 2: The fundamental method of face recognition using collections of images.

3.2. Face Detection (The Viola Jones algorithm)

The Viola-Jones algorithm is a popular technique for detecting faces in images and videos. Proposed by Paul Viola and Michael Jones in 2001, it is based on the Adaboost algorithm and Haar-like features.

To identify faces in an image, the algorithm utilizes Haar-like features, which are rectangular patterns of pixel intensities. These features are computed by taking the difference between the sum of pixel values in one rectangle and the sum of pixel values in another rectangle. The algorithm then performs a scan of the entire image using a sliding window, applying each Haar-like feature to every position and size of the window. This process allows the algorithm to efficiently detect potential facial regions within the image.

To speed up the detection process, the approach uses a cascade of classifiers, each consisting of a set of Haar-like features and a threshold. Only a small portion of the image is allowed to move on to the next step of the cascade, which quickly rejects parts of the image unlikely to contain a face.

The cascade of classifiers is trained using the Adaboost algorithm, where a weak classifier and a strong classifier are combined using machine learning techniques. In face detection, individual Haar-like features act as weak classifiers, while the cascade of classifiers serves as a powerful classifier.

The primary objective of the Viola-Jones algorithm is to create a cascade of classifiers from a group of training sets that can rapidly and accurately recognize faces in photos. Figure 3 illustrates the classroom instruction method.

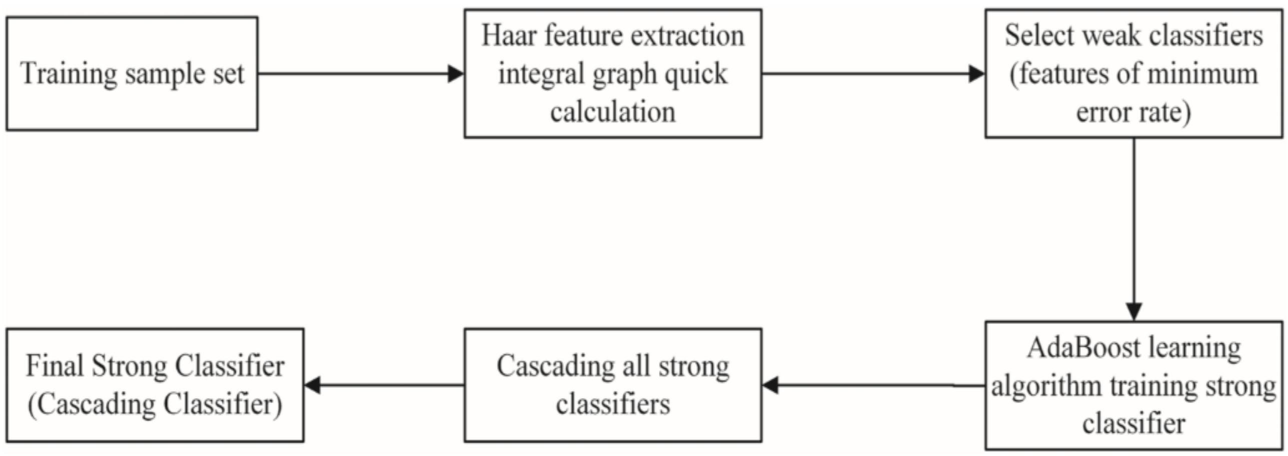

Figure 3: Process for training classifiers

3.2.1. Rectangular characteristics and haar features

Rectangle features and Haar features are two different kinds of feature descriptors utilized in computer vision applications. They were initially introduced in 2001[4] by Viola and Jones in their seminal study on face detection.

Each feature's value is determined by subtracting the sum of the pixel intensities in one rectangle from the sum of the pixel intensities in another rectangle. Haar features are rectangular patterns of pixel intensities. The simplest Haar feature is a two-rectangle feature, which consists of two adjacent rectangular regions, one white and one black. Other common types of Haar features include three-rectangle features, four-rectangle features, and diagonal features.

Haar features are used as a basis for many computer vision algorithms, particularly in the area of object detection. The Viola-Jones algorithm, for example, uses a cascade of Haar features to detect faces in images. Haar features have also been used in other applications, such as pedestrian detection, object recognition, and motion tracking[5].
Haar features are rectangular patterns of pixel intensities used in object detection and computer vision applications. They can take different shapes and sizes, and some common types of Haar features include:
The main types of Haar features are shown in Figure 4.

1. **Two-rectangle features:** This is the simplest type of Haar feature, consisting of two adjacent rectangular regions, one white and one black.
2. **Three-rectangle features**: This type of Haar feature consists of three adjacent rectangular regions, two of which are white and one of which is black.
3. **Four-rectangle features:** This type of Haar feature consists of four adjacent rectangular regions, two of which are white and two of which are black.
4. **Diagonal features:** This type of Haar feature consists of two rectangular regions that are diagonally adjacent, with opposite colors.
5. **Line features:** This type of Haar feature consists of a single line of rectangular regions with alternating colors.

Haar features are often used in combination with machine learning algorithms, such as AdaBoost, to classify objects and detect features in images. Different combinations of Haar features can be used to create classifiers for different objects or features of interest.

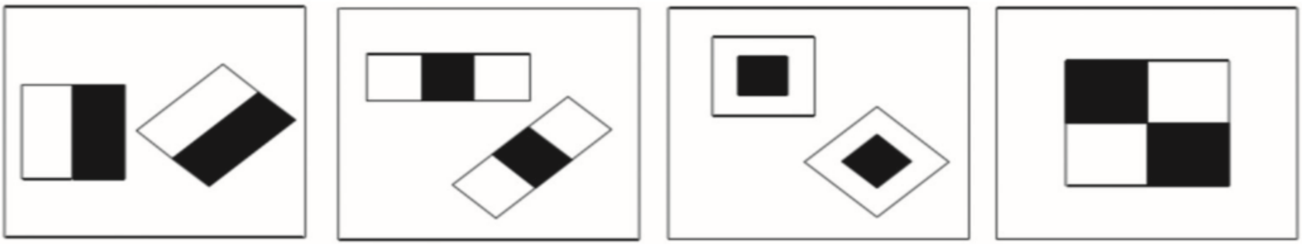

Figure 4: Haar features.

3.2.2. LBP-Based feature extraction

Local Binary Pattern (LBP) is a widely used technique for feature extraction from images. It was introduced by Ojala et al. in 1994 as a texture descriptor for image analysis. Since then, LBP has found applications in various computer vision tasks, including face recognition, object recognition, and texture classification.

The LBP algorithm compares each pixel in an image with its neighboring pixels and generates a binary code based on the comparison results. This binary code is then converted to a decimal number, representing the LBP value of the pixel. The LBP value provides information about the local texture pattern around that pixel.

For feature extraction, the LBP algorithm is applied to an image or a region of interest, generating a histogram of LBP values. This histogram represents the distribution of local texture patterns in the image or the region of interest and can be used as a feature vector to represent it.

LBP-based feature extraction has several advantages, including simplicity, robustness to noise and illumination changes, and computational efficiency. It can be computed using simple arithmetic operations and is insensitive to monotonic changes in illumination. Additionally, its computational efficiency makes it suitable for real-time applications.

In summary, LBP-based feature extraction is a widely adopted technique for texture analysis in computer vision. It generates histograms of local texture patterns, serving as feature vectors to represent images or regions of interest. LBP is known for its simplicity, robustness, and computational efficiency, making it suitable for various applications.

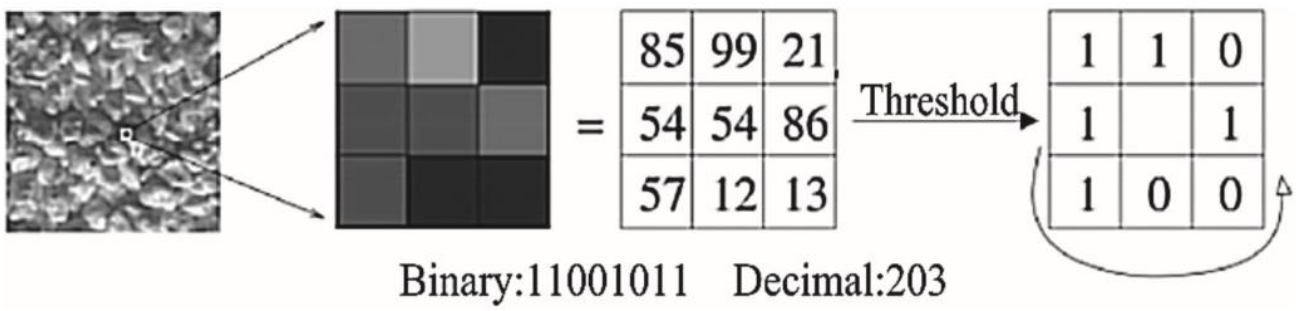

Figure 5: Local binary pattern (LBP) operator diagram.

3.3.1 Face recognition method based on image set

Face recognition methods based on image set refer to techniques that use a collection of face images rather than a single image to recognize a person. This approach is useful when dealing with variations in pose, illumination, expression, and other factors that can affect the performance of a face recognition system.

The basic process of face recognition based on image sets involves the following steps:

1. **Image Set Acquisition:** The first step is to acquire a set of face images for each individual in the database. The images should be captured under different conditions, such as different poses, expressions, and lighting conditions, to capture the variations in appearance.
2. **Image Set Alignment:** Once the image sets are acquired, the next step is to align them to a standard position and size. This is done to remove variations in pose, scale, and orientation, which can affect the performance of the recognition algorithm. Techniques such as Procrustes Analysis or Active Shape Models (ASMs) can be used for image set alignment.
3. **Image Set Representation:** The next step is to represent each image set as a feature vector. This can be done by computing statistical measures such as mean, covariance, or principal components of the images in the set. These statistics capture the variations in appearance within the image set.
4. **Feature Matching:** Once the image sets are represented as feature vectors, the next step is to compare them with the feature vectors of known individuals stored in a database. This is done to find the best match for the input image set. The matching algorithm can be based on various techniques such as Euclidean distance, Mahalanobis distance, or Support Vector Machines (SVMs).
5. **Recognition Decision:** Based on the similarity score between the input image set feature vector and the stored feature vectors, a recognition decision is made. If the similarity score is above a threshold, the input image set is recognized as a known individual, otherwise, it is classified as an unknown individual.
6. **Updating the Database:** If the input image set is recognized as a known individual, the database is updated with any new information about the individual, such as their name, ID, or any other relevant information.

In summary, face recognition methods based on image sets involve acquiring and aligning sets of face images, representing them as feature vectors, matching them with stored feature vectors, making a recognition decision, and updating the database. The performance of the recognition algorithm depends on the quality of the input image sets, the accuracy of the feature extraction, and the effectiveness of the matching algorithm.

3.3.2 Random Forest Technique in Face recognition

Random Forest (RF) is a popular machine learning technique used in face recognition. It is an ensemble learning technique that mixes various decision trees to increase prediction accuracy.
In face recognition using Random Forest, the basic process involves the following steps:

1. **Feature Extraction:** The first step is to extract features from the face images. These features can be obtained using techniques such as Local Binary Patterns (LBP), Histogram of Oriented Gradients (HOG), or Deep Convolutional Neural Networks (CNNs).
2. **Feature Selection:** Once the features are extracted, the next step is to select the most relevant features that can discriminate between different individuals. This is done using techniques such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA).
3. **Training the Random Forest Model:** The next step is to train the Random Forest model using the selected features and a set of labeled face images. The Random Forest model creates multiple decision trees, each of which is trained on a random subset of the training data.
4. **Testing the Model:** Once the Random Forest model is trained, it is tested on a set of test images to evaluate its performance. The test images should be different from the training images to ensure that the model can generalize well to new data.
5. **Recognition Decision:** Based on the predictions of the individual decision trees in the Random Forest model, a recognition decision is made. If the majority of the decision trees predict a particular individual, that individual is recognized.
6. **Updating the Model:** If the recognition decision is correct, the model is updated with any new information about the individual.

The Random Forest technique has been shown to achieve high accuracy in face recognition tasks, particularly when combined with effective feature extraction and selection techniques. It can also handle many features and is robust to overfitting, making it a popular choice for face recognition applications.

3.3.3 Face Analysis SVM (Support vector machine)

A popular machine learning method called Support Vector Machine (SVM) is utilized in face analysis for tasks like face detection, facial expression recognition, and age estimate. A high-dimensional feature space is divided into data points belonging to several classes using the supervised learning technique SVM.

In face analysis using SVM, the basic process involves the following steps:

1) **Feature Extraction:** The initial step is to take the face photos and extract the features. These features can be produced by employing methods like Deep Convolutional Neural Networks (CNNs), Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP).
2) **Feature Selection:** Once the features are extracted, the next step is to select the most relevant features that can discriminate between different classes (e.g., different facial expressions or age groups). This is done using techniques such as Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA).
3) **Training the SVM Model:** The next step is to train the SVM model using the selected features and a set of labeled face images. The SVM model learns a decision boundary that maximally separates the data points of different classes.
4) **Testing the Model:** The SVM model is evaluated on a collection of test images once it has been trained to assess its performance. To make sure that the model is capable of generalizing adequately to new data, the test images should differ from the training images.
5) **Recognition Decision:** Based on the output of the SVM model, a recognition decision is made. For example, if the SVM model is trained for facial expression recognition, it can classify the test images into different facial expression classes.
6) **Updating the Model:** If the recognition decision is correct, the model is updated with any new information about the individual.

SVM has been shown to achieve high accuracy in face analysis tasks, particularly when combined with effective feature extraction and selection techniques. It can also handle non-linear decision boundaries and is robust to overfitting, making it a popular choice for face analysis applications.

IV WORKING MODEL PROPOSED HYBRID TECHNIQUE

"In our research, we suppose that the Focus camera's face images can be recognized, and the facial data will already be available for estimation. The grain is generated using a face identification approach like the Viola-Jones method. The problem of handling various facial expressions, brightening circumstances, and facial orientations is solved in the suggested model. The model involves an equation for facial recognition and facial characteristics in the center of the image.

Photo sets are defined at fixed angles based on the degree of human face freedom, with 'Normal' being an equal-level image. The picture pre-processing stage is implemented using the image pyramid parameters. For feature extraction from the b-features images, SVM classification is used, although LBP (Local Binary Pattern) can be extremely sensitive to spatial noise and appearance. If the quality is labeled 1 without the SVM class, the original picture is set to 1 or 0. It is vital to label the image attribute as 0, otherwise, a Random Forest is used to compute and calculate labeled extraction activity using the approach.

During training, the desired settings are saved on the internal node when configuring a random tree. The root node uses the highest parameters to retrieve data, and for each succeeding node, the identical action is repeated. To extract random training patterns from each image sequence for each tree, we employed a package. Training is stopped when the requirements for completion are met, allowing for dependable performance outcomes versus roadways for data collection.
In conventional Random Forest (RF) training, the tree will stop growing if it reaches a maximum depth or if the current node contains insufficient data. We will exhibit the experimental results under various situations after adjusting the minimum sample size of nodes and the maximum depth of the tree."
Please note that some parts of the text may still require further clarification or context for a better understanding of the research being described.

Steps for the proposed algorithm:

1. Three by three matrices are loaded with the 100-image database.

2. After that, choose at random to look for a photo. A new database of 399 photographs was then established after the image from the matrix of 100 images was removed.

3. A analogous matrix is produced by subtracting the results of 99 photographs from the photos.

4. Correlation Matrix Eigen vector computation. Therefore, let's say that we took 20 photos for which the Eigen vectors are tallied, and that the photographs' signatures are counted with various facial expressions and a dimension of 205x274px.

5. The image is then searched using the Eigen vector, and the results are matched using the shortest possible Euclidean distance. The output is the image with the closest distance.

6. In this study, we assessed how quickly 99 photos were recognized overall and for each individual photo.

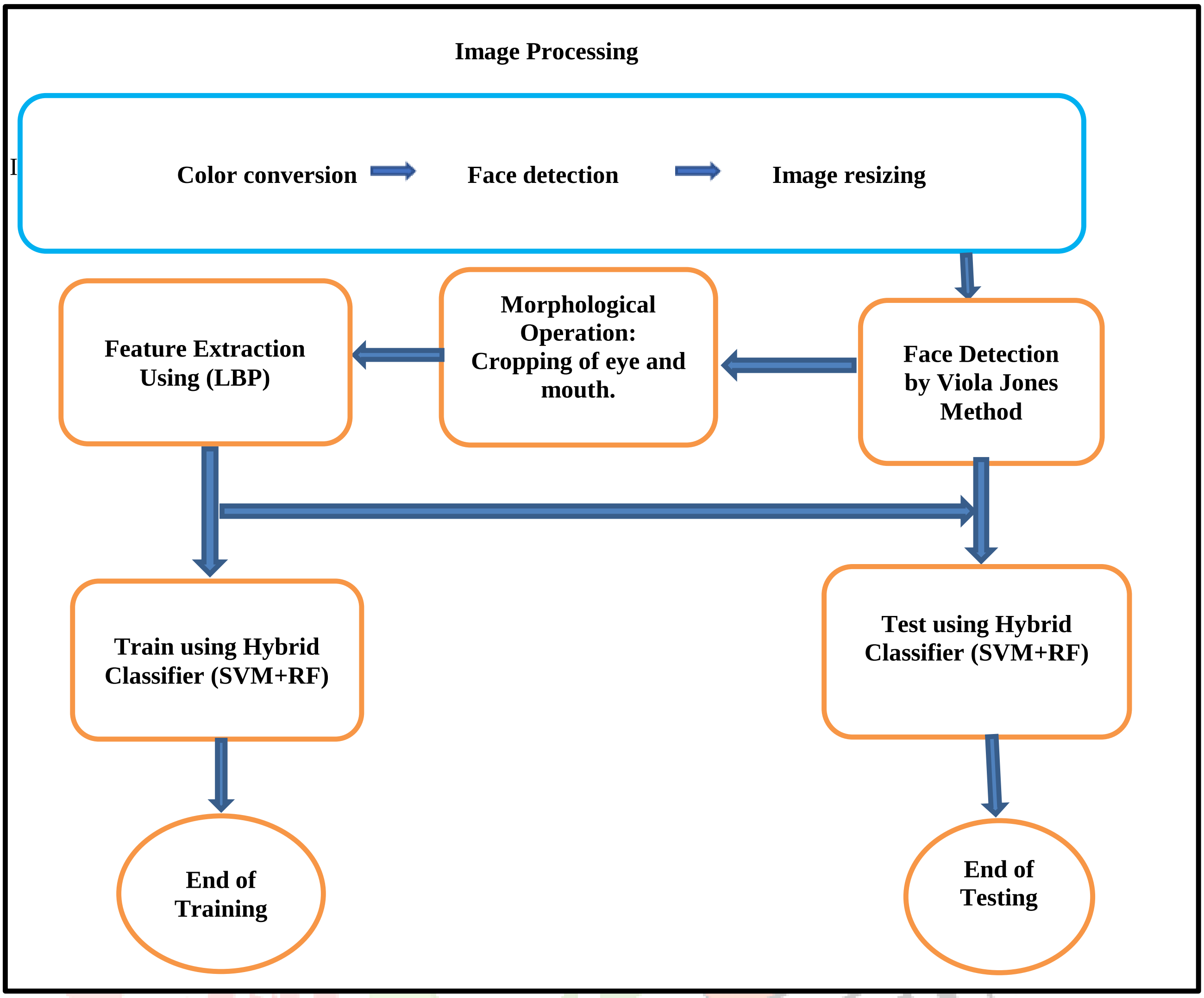

Figure 6: SVM+ Random Forest (Proposed Model)

4.1 Result and discussion

After dividing the 400 photos into five satellites, we randomly tested the 400 photographs. 20 images from Subsystem 1 show two people with ten other people. Substitute 2 features 40 photographs, including 10 images of 4 individuals. 70 photographs, 7 photos, and 10 photos make up Replacement 3. 120 images from 12 subjects make up Subset 4 while 150 images make up Subset 5. The table below displays the test acceptance rates and test durations:

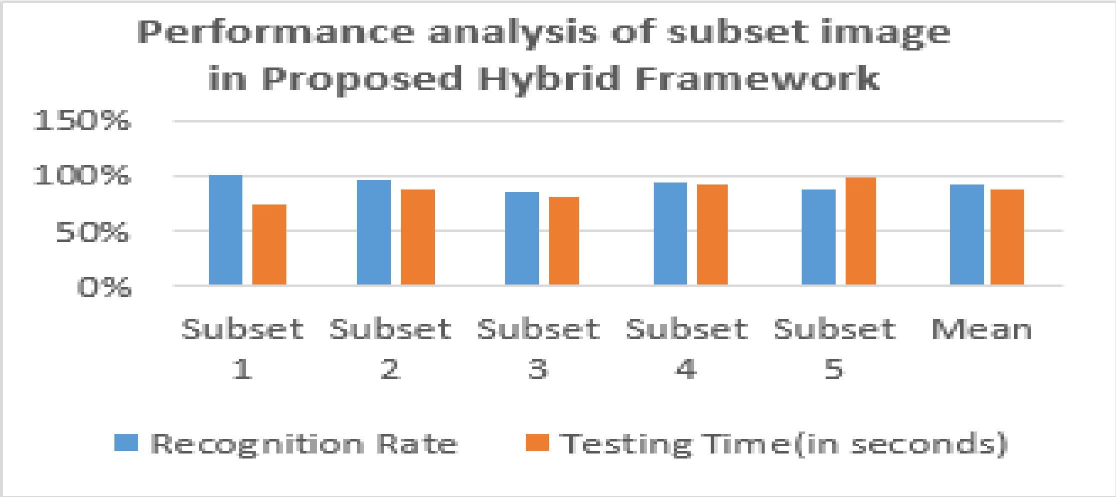

Figure 7: Result from proposed algorithm (400 images)

Used Approch	Mean Recognization Of Rate
Optimazed SVM/RF RF SVM (liner Kernal) SVM (rbf Kernal)	96.6% 94.74% 96.10% 94.74%
LBP (Face Discription with Local Binary pattern: Application for facerecognization)	94.6%
RF	92%
SVM	95%
RF+SVM(Proposed Hybrid model)	98.99%

4.1.2 Comparison with Previous Approach and proposed approach

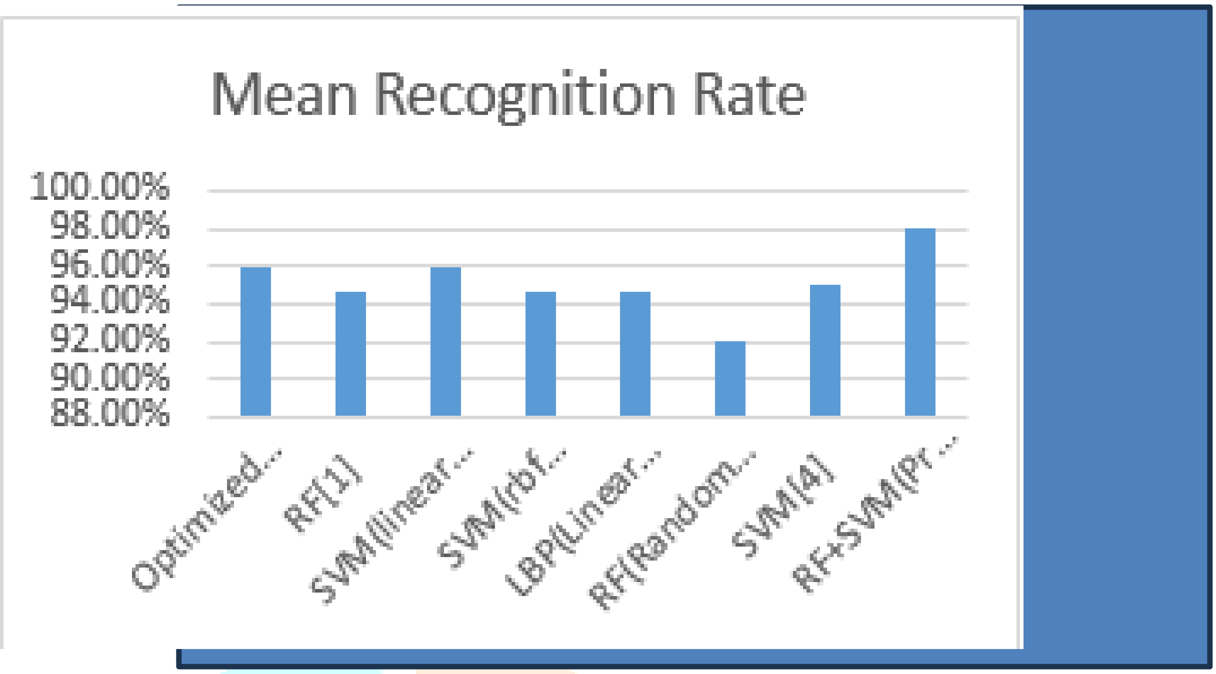

Figure 8: Recognition Rate Comparative Analysis

IV. Conclusion

The study presents an innovative facial recognition method suggestion. This audit's proposed methodology combines RF analysis and SVM. The suggested RF + SVM technique considerably increases the recognition rate. The process starts by extracting features and using SVM to calculate eigenvalues for differential regression analysis. In this approach, the synthesis of many motions and expressions contributes to a greater level of face recognition. It contains a detailed analysis of our algorithm's out-of-date behavior. A database that is accessible online for free shows all tests. The test makes use of 400 images including 10 distinct individuals. The study advances our knowledge of the significance of facial recognition in RF and SVM. This technique is extensively applicable for finding patterns. This combination strategy has numerous applications, including Irish identification and Face recognition.

The usage of facial editing techniques for feature elements may eventually involve the introduction of numerous databases for more accurate outcomes. A great method for deleting page features is to use page properties.

Future research in the field of facial recognition using the proposed RF + SVM technique could explore several potential changes and advancements:

1. Dataset Diversity: The current study used a relatively small dataset with 400 images and 10 individuals. Future research could focus on using larger and more diverse datasets with a broader range of facial expressions, lighting conditions, and ethnicities. This will help to improve the generalizability and robustness of the proposed method.

2. Deep Learning Approaches: As deep learning techniques continue to advance, future research could explore the integration of deep neural networks in facial recognition. Convolutional Neural Networks (CNNs) have shown remarkable performance in image recognition tasks and could be utilized to enhance the feature extraction and classification stages of the proposed method.

3. Real-time Implementation: To further extend the practical applicability of the proposed technique, researchers could focus on optimizing the algorithm for real-time performance. This would involve reducing computation time and memory requirements, enabling the method to be deployed in real-time applications such as surveillance and security systems.

4. Privacy and Ethical Considerations: As facial recognition technology becomes more widespread, it is essential to address privacy and ethical concerns related to its use. Future research should investigate methods to ensure the responsible and secure use of facial recognition systems, including measures to protect individual privacy and prevent misuse.

5. Adversarial Attacks: Investigating the vulnerability of the proposed technique to adversarial attacks could be an interesting avenue for future research. Adversarial attacks involve deliberately modifying input data to mislead the recognition system, and understanding and mitigating such vulnerabilities are crucial for ensuring the system's reliability.

6. Multi-modal Recognition: Combining facial recognition with other biometric modalities, such as fingerprint or iris recognition, could lead to more robust and accurate identification systems. Future research could explore the integration of multiple biometric features to enhance the overall recognition performance.

7. Human-Centric Evaluation: In addition to technical evaluations, future research could also focus on human-centric evaluation methods to assess the usability and user acceptance of the proposed technique. Understanding users' perceptions and experiences with the system can provide valuable insights for further improvements.

In conclusion, future research in facial recognition could address various aspects to advance the proposed RF + SVM technique, including dataset diversity, deep learning integration, real-time implementation, privacy considerations, defense against adversarial attacks, multi-modal recognition, and human-centric evaluations. These endeavors would contribute to the continued development and refinement of facial recognition technology for practical and ethical applications.

REFERENCES

[1] Liu, Q., Chen, L., & Chen, S. (2015). Adaptive local binary pattern for face recognition. Journal of Electronic Imaging, 24(5), 053006.

[2] Zhang, L., Liu, Z., & Zhang, D. (2010). A review on multi-scale local binary pattern in face recognition. Proceedings of the 2010 Fifth International Conference on Image and Graphics, 2, 357-361.

[3] Wang, L., & Wang, Y. (2016). An efficient face recognition approach using LBP and SVM. Journal of Computational and Theoretical Nanoscience, 13(5), 3265-3271.

[4] Bhattacharyya, D., Das, P., & Nasipuri, M. (2016). A fast and efficient face recognition system using local binary patterns and KNN. Pattern Recognition Letters, 70, 10-16.

[5] Viola, P., & Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. In Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001 (Vol. 1, pp. I-I).

[6] T. Ojala, M. Pietikainen, and T. Maenpaa, "Multiresolution gray-scale and rotation invariant texture classification with local binary patterns," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 24, no. 7, pp. 971-987, 2002

[7] T. Ahonen, A. Hadid, and M. Pietikainen, "Face recognition with local binary patterns," in Proceedings of the European Conference on Computer Vision, Graz, Austria, May 7-13, 2006, pp. 469-481.

[8] G. Zhao and M. Pietikainen, "Dynamic texture recognition using local binary patterns with an application to facial expressions," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 29, no. 6, pp. 915-928, 2007.

[9] M. Heikkila, M. Pietikainen, and C. Schmid, "Description of interest regions with local binary patterns," Pattern Recognition, vol. 42, no. 3, pp. 425-436, 2009.

[10] A. O. Boudraa and H. F. Li, "Local binary patterns and their application to facial analysis: a survey," IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 42, no. 4, pp. 481-494, 2012.

[11] Vu, N.-S., Exploring patterns of gradient orientations and magnitudes for face recognition. IEEE Transactions on Information Forensics and Security, 2013. 8(2): p. 295-304

[12] Vu, N.-S. and A. Caplier, Face recognition with patterns of oriented edge magnitudes, in ECCV. 2010.

[13] Liang, Y., et al., Exploring regularized feature selection for person specific face verification, in ICCV. 2011.