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Gender Detection using Facial Features with Support Vector Machine

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***Abstract*—Innovative security technologies have increased the need for accurate identification. Gender identification has been widespread use of image analysis in recent decades. The face is one of the most popular biometric features in image processing. In Image Processing and video surveillance, systems that automatically discern gender from facial photos are gaining prominence. This study discusses face traits and gender categorization. In this study, we created a technique with good runtime and efficiency to determine human gender using face photos. It uses characteristics taken from pre-processed face photographs of various ages. Support Vector Machine (SVM) Classification was used to determine class thresholds. Our method classifies UTK-FACE gender with 91.63% accuracy.**

Keywords—Face Landmarks, Feature Extraction, Support Vector Machine, Binary Classifier, Gender Identification.

I. Introduction

Image processing and machine learning are employed in gender categorization [1] and facial expression recognition [2]. In recent decades, computers have grown famous for recognizing human faces' ethnicity and gender [3]. Therefore, image processing plays a large part in computer science domains such as surveillance, biometrics, and security [4]. Gender recognition from face photographs is a hot topic [5]. Gender detection is a challenging biometrics field [6]. Faces of Indians, Chinese, Japanese, Africans, and Americans fluctuate with their inter-ocular distance and other facial traits, which affects gender classification. Image processing uses gender-recognition algorithms. Surveillance camera footage is analyzed to recognize suspicious faces. The fundamental problem of these systems is looking for a match between an input facial image and millions of samples in a reference database [7]. Figure 1 displays gender categorization for massive face databases—the time needed to search a reference database for a face image match. First, determine the gender (0/1) and maybe ethnicity [8] of the provided face, then compare with the database. Gender detection from facial photos may seem easy, but humans sometimes struggle.

This study examines the human face. All supervised learning pattern recognition issues may be divided into the following phases. Face preprocessing, feature extraction, classification. Step 1 detects and crops the human face. Pre-processing, such as Normalization, follows. In step 2, a feature vector was taken from the image (the nose, eyes, mouth, and L/R ears) to get the most accurate face feature. Finally, image feature vectors are used to categorize image gender automatically. The support vector machine categorizes subjects as male or female. Below are general steps for mechanical face image issue solving.

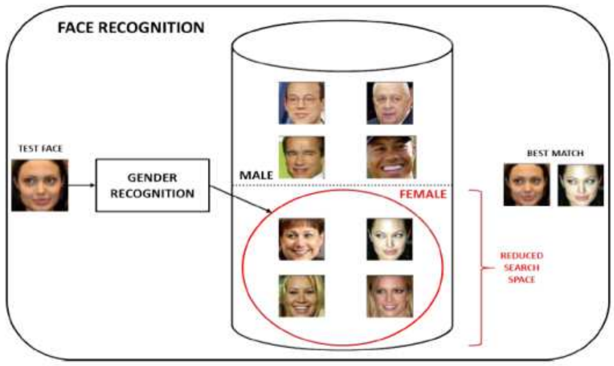

Fig. 1. Examples of Gender Recognition Applications

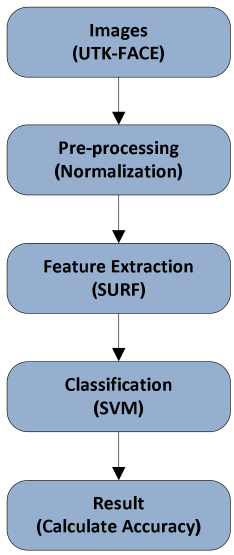

Fig. 2. The General System of Gender Classification (GSGC)

Figure 2 illustrates the General System of Gender Classification (GSGC).Existing face detection algorithms work well on frontal faces, but accuracy declines with angled faces. Facial features can also determine gender. Pose modifications and partial facial occlusions, such as scarves, hats, and glasses, are the most difficult: gender, ethnicity, and

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expression impact gender recognition algorithm performance. Wrinkles on older women's faces may resemble those of males. The main objective of our work is to find the gender as Female or Male through the SVM classifier by extracting features from facial landmarks circles through Speeded Up Robust Features (SURF) based feature descriptor.

II. RELATED WORKS

Many researchers have created gender-classification methods. Most of these procedures involve extracting and fusing face characteristics like:

Azzopardi et al. [7] examined gender classification. Using domain-dependent SURF (speeded up robust features) descriptors and trainable COSFIRE filters. GENDER-FERET, LFW, and UNISA-Public are gender detection databases. GENDER-FERET has 94.1% accuracy, UNISA-Public 89.9%, and LFW 99.3%. CROSSFIRE and Viola-Jones. Simple, effective. The algorithm may be tested on different faces. CROSSFIRE-based solutions may be utilized without subject knowledge.

Rahman et al. [9] created BUET. Naive Bayes classifies the database's gender with 86.6% accuracy. Picasso was used to extract the mean face; histogram equalization was applied to improve similar frontal face density areas. 15-60, 5-year intervals. One technique extracts attribute based on color, frequency, texture, or shape. Eye and lip frontal face identification coordinates estimate cheeks and forehead. They are fascinating. This has several applications. Such research might improve age and gender estimation.

Mohammed et al. [1] used eyes, nose, mouth, and SUMS and T&T databases to categorize face pictures by gender. SUMS and T&T both score 98.75%. A binary classifier, such as K-Nearest Neighbors (KNN), support vector machine (SVM), Adoboost', neural networks, and Bayesian classifier, is used for gender categorization using machine learning. CNN uses backpropagation learning. This paper includes preprocessing, face detection, feature extraction, and classification. Face recognition is cheaper than pixel-based gender classification. Presents gender identification methodologies and algorithms for enhanced categorization. It covers gender identity research. Gender identification is challenging in unrestrained contexts.

A. Saxena et al. [6] developed a gender and age detector using Deep Learning. Accurate forecasts and quick outcomes. Kaggle.com's dataset produced correct findings. This dataset helps train models. We picked this photo-rich dataset. This dataset provides more diverse data, boosting algorithm performance. Age and gender will be determined using more images. Real-time gender and age will be determined.

Q. Deng et al. [10] created a new face dataset. Using this complete information, they build a gender classifier. They scored 98.67% on wild faces, the most complex public database (LFW). The wild Chinese database has 10,000 Internet photos. This study analyses gender recognition and dataset changes. Their model is not constrained. Unlike typical approaches, we consider the whole dataset. Our model improves with more data. This paper describes creating a new comprehensive dataset. Future networks and datasets will be increasingly complicated.

Levi et al. [11] studied gender classification. They quickly examine essential approaches and offer a rudimentary convolution net architecture. Their approach outperforms state-of-the-art age and gender estimation methods. Using Internet data, we evaluate deep CNN's face recognition. Clean deep-learning architecture minimizes overfitting from poor labeling. Our network topology, "shallow" CNN, can improve age and gender classification even with tiny picture sets. Second, our model's simplicity implies that complex systems with additional training data may enhance outcomes.

III. METHODOLOGY

Figure 3 shows the proposed approach's workflow, comprising input pictures, pre-processing, feature extraction, and classification training. Training and testing are system operations. SURF-based image features learn and store data. Preprocessing normalizes photos. Preprocessed pictures with Ground table Landmarks are sent to SURF to extract feature descriptor vectors. SURF-based feature descriptors are sent through a binary-class SVM classifier to determine gender.

Normalized pictures have facial landmarks added using a ground truth table. SURF feature descriptors extract features using Ground Truth Table Landmarks. After collecting SURF features, a Binary-class non-linear SVM classifier is used to categorize Gender Detection as Male/Female.

A. Pre-processing

Image preprocessing improves analysis. Faces have a shadow- or brightness-based illumination—light and shadows obscure face features. Preprocessing reduces distortions and boosts application-specific properties. This approach normalizes. Most ML algorithms need similar-sized photos.

Normalizing images impacts pixel intensity ranges. It turns a picture into pixel values. The camera records the face from different perspectives. The image blurs and darkens. We will normalize an image's pixels.

B. Feature Extraction

Feature extraction consists of landmarks on the image and tracks significant locations of eyes, nose, and mouth in an image [12]. The SURF descriptor extracts face image characteristics using 68 facial landmarks from the Ground table. Here we depict the Face landmark using the ground table. SURF descriptor uses the Face landmarks and extracts the descriptor vectors.

Face Landmark Detection: Face landmark detection identifies important facial regions. Facial landmark identification helps identify a face's landmarks. Face landmarks are used [13]. Facial landmarks are used for face alignment, posture assessment, face switching, blink detection, and sleep detection. The trained facial landmark detector calculates 68 (x, y) face structure coordinates. Figure 4 displays 68 coordinates.

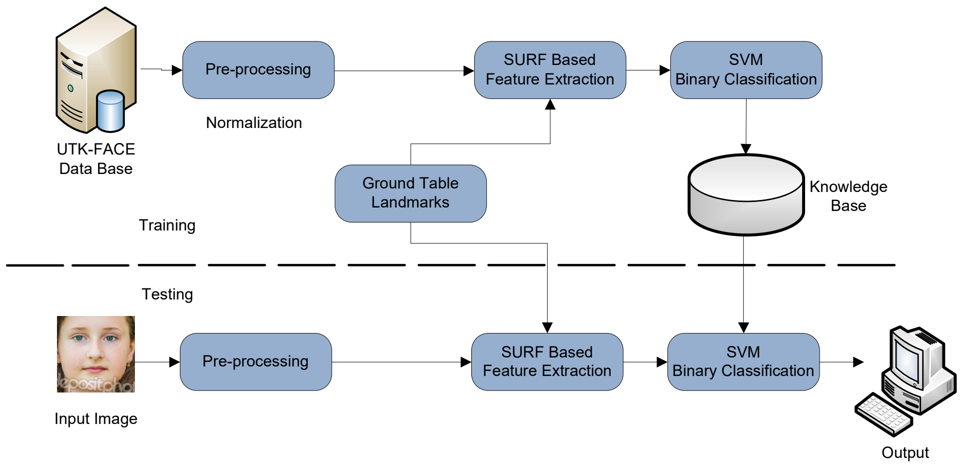

Fig. 3. Block Diagram

1) *SURF-Based Feature Descriptor:* Speeded Up Robust Features (SURF) detects and describes local computer vision. SURF descriptors can locate items, people, and faces, track objects, and extract regions of interest. Feature descriptors define picture features completely.

Fig. 4. Facial Landmarks

First, a landmark circle is used to extract the SURF feature descriptor. Next, we compute the inner 68 facial landmarks' (68x2)=136 SURF features, including eyes, nose, mouth, and L/R ears. Figures 4 and 5 show two fiducials. Each facial picture is given a (68x128)-element feature vector. Finally, we train an RBF- kernel SVM classifier.

Fig. 5. Representation of the Proposed Face

Blue dots denote face landmarks. These landmarks are sent to SURF to extract feature descriptors, and the SVM Classifier classifies the Gender.

The below Algorithm 1 callout gender identification as Female or Male and the SURF-based feature descriptors steps are also explained in the algorithm as,

Algorithm 01: SURF Based feature descriptors.

Inputs: Input Face Images.

Output: Gender Identification as Male or Female.

Step.1	*Initial, by applying Normalization to the input face image.*
Step.2	*Applying facial landmarks on each separated face image is adopted around the center of face images throughout the UTK-Face database image with the help of the ground truth table.*
Step.3	*Computing SURF-based feature descriptors to extract the face descriptor.*
Step.4	*After extracting the face descriptors from the SURF-based feature descriptors, the extracted vector descriptors pass to the SVM-Classifier to classify the gender.*
Step.5	*SVM-Classifier classifies the gender by using the Binary classification and RBF-Kernel classification.*
Step.6	*The output of the SVM-Classifier is the classification of the gender as Female or Male.*

C. Classification

SVM can distinguish faces, differentiate postures and identify [14]. Figure 6 shows the classification flow. Face landmarks, SURF feature descriptors, and RBF-kernel SVM classifier are trained. Machine Learning teaches machines to perform like humans using past data and projections. Supervised learning labels inputs and outputs. Supervised learning predicts future occurrences using experience and tagged examples. Face classifier training and testing use cross-validation. Labeling images improve SVM gender classification [15].

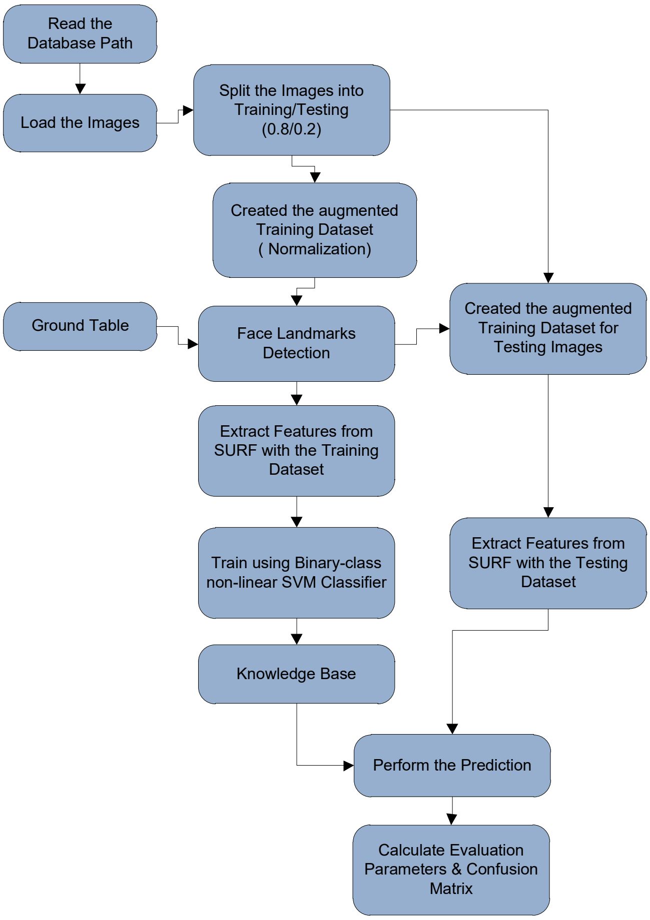

Fig. 6. Classification Flowchart

Support Vector Machine (SVM) is a Classification and Regression Supervised Learning approach. SVM categorizes new data points by constructing the best decision boundary (with the highest margin). SVM develops the best line or decision boundary to split n-dimensional space into classes so new data points may be easily placed. Database features dictate hyperplane dimensions. Hyperplanes maximize margins. It limits data-point distance. Find an n-dimensional hyperplane. The kernel calculates x-n/x-m distances. Closer data points score better. Figure 7 shows SVM two-class grouping.

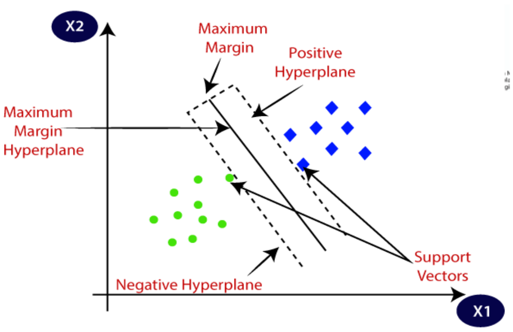

Fig. 7. Support Vector Machine (SVM) Data Grouping

Dual-class SVMs perform best. Gender detection is male and female. RBF kernels are used in techniques like SVM classification. For SVM classification, RBF finds non-linear classifiers and regression lines. Equation 1 shows the RBF kernel.

$$K(x, x') = \exp\left(-\frac{\|x-x'\|^2}{2\sigma^2}\right) \tag{1}$$

Where $\|x - x'\|$ may be recognized as the squared Euclidean distance between the two feature vectors. 'σ' is a free parameter. An equivalent definition involves a parameter $\gamma = \frac{1}{2\sigma^2}$ Where 'γ' is a parameter that sets the "spread" of the kernel.

Using the training pictures to learn SVM with a non-linear (RBF) kernel, the final layer identifies a test image as male/female. SVM-RBF best classifies face pictures, while SVM classifies gender [16]. Figure 8 shows the SVM Male/Female classification.

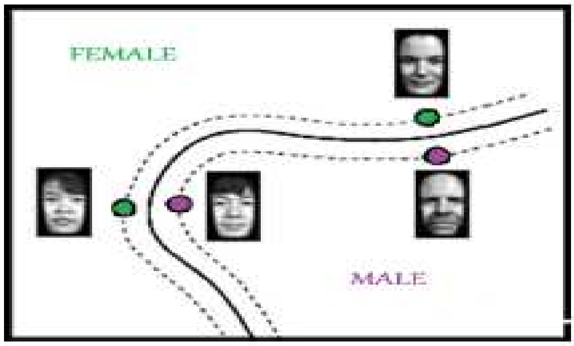

Fig. 8. SVM classification Grouping as Male/Female

For the above training, test data or photos are included for categorization. Test data or photos assess classification performance characteristics: Pre-processing, feature extraction, and SVM classifier, process testing data.

IV. Results and Discussion

This part describes the proposed technique's database, experimental setup, and outcomes.

A. Database Description

In this study, we employ UTK-FACE [17]. This database compares face photos. UTK-FACE Database comprises 23,708 pictures. Only frontal faces are studied [18]. This database trains and tests gender recognition algorithms. Figure 9 shows UTK-FACE faces (Female and Male). Each row has baby, younger, and adult facial photos.

Female Images

Male Images

Fig. 9. Examples of faces from UTK-FACE Database Images

To standardize, we utilize the UTK-FACE database, which comprises equal numbers of male and female face photos [9]. The database includes gender, posture, and race-specific frontal faces [19]. Our training and testing sets were randomly chosen. To maintain the database before gender distribution, we collected 23,360 male (11,870) and female (11,490) face photos in both sets. Face pictures were developed for training and testing. To quantify performance, we split face photos into training and testing sets.

B. Experimental Setup

Intel core i7 CPU with 10th generation, Windows-10 (64 bit), and Nvidia GTX graphics card with 8GB RAM [20].

C. Performance Evaluation

Specificity, accuracy, precision, recall, F-1 score, and ROC curve assess model performance. Specificity, accuracy, precision, recall, and F1 score are represented in Equations 2, 3, 4, 5, and 6.

$$\text{Specificity} = \frac{\text{TrueNegatives}}{\text{TrueNegatives+FalsePositives}} \tag{2}$$

$$\text{Accuracy} = \frac{\text{TotalnumberofCorrectPredictions}}{\text{TotalnumberofPredictions}} \tag{3}$$

$$\text{Precision} = \frac{\text{TruePositives}}{\text{TruePositives+FalsePositives}} \tag{4}$$

$$\text{Recall} = \frac{\text{TruePositives}}{\text{TruePositives+FalseNegatives}} \tag{5}$$

$$\text{F1\_score} = 2 * \frac{(\text{Precision}*\text{Recall})}{(\text{Precision}+\text{Recall})} \tag{6}$$

Table 1 provides the Results and Analysis of quantitative criteria, including accuracy, precision, sensitivity, and specificity used to measure the recommended model's performance.

TABLE I. RESULTS AND ANALYSIS

Performance	Results (%)
Accuracy	91.63%
Sensitivity	91.27%
Specificity	91.97%
Precision	91.59%
F1_Score	91.43%

The confusion matrix shows an algorithm's efficacy. Columns reflect facts, rows anticipated ones. Figure 10 displays the SVM Classifier's ROC curve, and Figure 11 shows the two classes' confusion matrix.

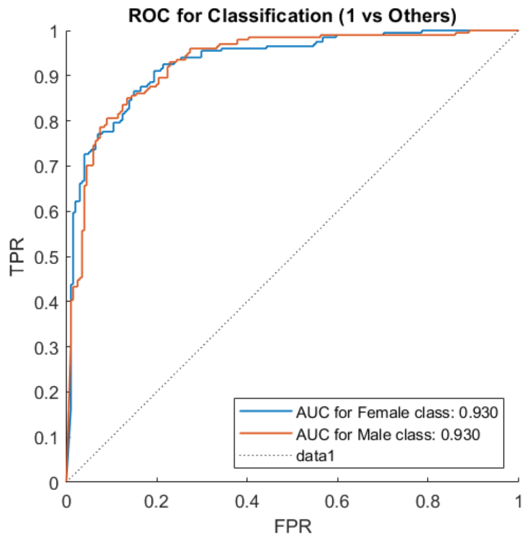

Fig. 10. ROC for SVM Classification

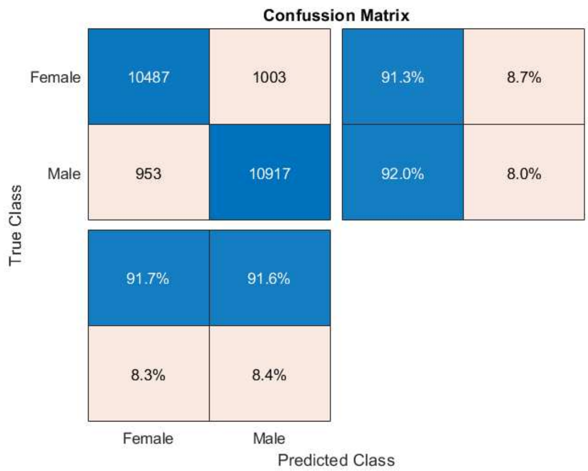

Fig. 11. Confusion Matrix

D. Comparison with SURF-based results

SURF is parameter-free. Table 2 shows the proposed method's UTK-FACE accuracy (91.63%). Table 2 compares the proposed method and database with two different methods and databases. Table 3 compares the proposed model database's performance with other UTK-FACE databases.

TABLE II. COMPARISON WITH OTHER METHODS AND DATABASE

Database	Method	Accuracy (%)
GENDER-FERET [7]	SURF-Based	89.2%
Buetfacial[9]	Canny Edge Detection	86.6%
UTK-FACE Proposed	SURF-Based	91.63%

TABLE III. COMPARISON WITH OTHERS UTK-FACE DATABASE

Database	Gender Accuracy (%)
UTK-FACE [17]	90.35%
UTK-FACE [18]	80.34%
UTK-FACE Proposed	91.63%

For the proposed UTK-FACE database, our algorithm achieves an accuracy of 91.63%.

V. CONCLUSION

Computers can now discern gender. Comparing machine learning detection, extraction, and classification approaches with a binary-class non-linear SVM classifier improves face gender recognition accuracy. Images may show gender-specific facial features. After training, retrieved SURF features using pre-processed pictures to determine gender using binary-class non-linear SVM algorithm. Simple, effective. Using pre-processed data or pictures, the algorithm's accuracy is 91.63%.

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