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EDUCATION & TRAINING

Extract Features from Periocular Region to Identify the Age Using Machine Learning Algorithms

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Abstract
Latest studies done on huge data collected from aging features proved that the performance of facial image based age estimation is low and need to be improved. One of the significant biometric traits for human recognition or search is Human age. Age assessment is very much exigent over other pattern recognition problems since the aging differs from person to person. This paper proposes a new framework that uses periocular region for age feature extraction and application of hybrid algorithm for age recognition. Firstly, preprocessing and periocular region normalization is done to acquire age invariant features. Secondly, the periocular region that underwent preprocessing is analyzed using hybrid approach, a novel machine algorithm that combines both SVM and kNN. The proposed technique generates the best recognition outputs.

Keywords Periocular region · Features extraction · Age assessment · BIFs · AAM

Introduction

These days, a lot of research is going on finding new and novel techniques to maximize the performance in estimating the human age based on facial images as these are required in many applications like demographic analysis, visual surveillance, commercial user management, and aging progression [1]. One of the significant biometric traits for human recognition or search is Human age. Estimating the human age by taking a facial image into consideration is too intricate for humans [3]. This situation lead many researches in gaining curiosity to implement automated age estimation tools to assess human age range or age from facial images. Security control, Human Computer Interaction and law enforcement are a few latent applications of automatic age estimation. Automated age estimation models are majorly facing issues with extracting effective aging features from a facial image [10]. In the earlier decade, many efforts were done on representing aging features. Initially, texture features like skin wrinkles and simple geometry features such as distances between eyes and nose were taken up [5]. Later, BIF (Biologically Inspired Features) [6] were added and extensively adopted in age estimation applications. In recent years, ST (Scattering Transform) [7] was introduced as betterment to BIF by toting up filtering routes and is expected to enhance further through manifold learning such as OLPP (Orthogonal Locality Preserving Projection) in near future [8]. Estimator is another crucial component in age estimation tool. In general, age estimation can be either characterized as a regression or a classification problem. Literature included regression methods like Support Vector Regression (SVR) [6], multi-instance regression [11] and quadratic regression [8]. In recent times, human age estimation tools was applied on large-scale facial data in order to extract aging factors by using a deep learning technique namely CNN (Convolutional Neural Networks) [12]. For classification models Support Vector Machines (SVM) [6], k Nearest Neighbors [9] and Multilayer Perceptrons [7] were included. Though experimental results proved that these deeply-learned aging patterns succeeded in enhancing performance on both unconstrained photos [14] and benchmark datasets [13] on the other hand, multiclass classification ignored the ordinal information in age labels completely and regression over-simplified it by treating it as a linear model where as human aging pattern is nonlinear in

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Fig. 1 Sample Dataset of Periocular Region Images of different age groups

common. It is simple to asses where a person is elder or younger than a specific age while a person predicts a human's age. So, techniques similar to cost-sensitive ranking have recently been added to age estimation [7]. In this paper, we propose a new framework of utilizing periocular region and application of hybrid algorithm SVM-kNN on preprocessed periocular region for age recognition. Experimental results show that our proposed approach yields the best recognition outcomes and higher classification rate with lower error rate than that of traditional SVM and kNN.

Related work

Many of the present techniques use a two-step approach in assessing the age of a human from a face image. In this, the first step is local feature extraction and the second step includes multi-class classification. The texture and geometry features thus extracted are utilized in distinguishing the human into baby or adult or senior. Many of these techniques are anticipated from AAM model [15], a natural tool in modeling the shape and texture of a face image in parallel [16, 17].

BIFs, Bio-inspired Features are considered as the most unbeaten features in estimating human age [18]. These features are used in performing age classification as well as regressions. Fu and Huang [19] applied quadratic regression and discriminative manifold learning towards age estimation.

Guo et al. proposed loads of regression methods like CCA, SVR and PLS to estimate the age of facial image [20, 21]. Yang et al. employed a single hyperplane ranker namely Rank Boost algorithm to predict human age [22].

Chang et al. [23] introduced OR-SVM, a parallel hyperplanes model [24] to estimate age and further extended is model to even non-parallel hyperplanes [25] to make it more flexible. Since, object detection and image recognition became possible with deep learning methods, age estimation [37] can also be easily achieved with some simple modifications like by adding CNN to these methods.

Yi et al. [26] initially recommended CNN in estimating human age from facial images. But, however, the suggested CNN technique is not sufficient in achieving best results as it contains only 4 layers (convolution, pooling, local layer, full connection). A subset of MORPH II that includes 10 K facial images is used to test the shallow CNN. So, at present, in [27] a relatively deeper CNN is introduced for age estimation. The newly proposed model also uses CNN to haul out features which are then applied on another regressor to generate final age prediction.

Herbrich et al. [28] implemented a novel ordinal regression technique namely support vector learning. In [29], Singer and Crammer proposed a perceptron ranking (PRank) algorithm for ordinal regression which achieved in generalizing the online perceptron algorithm by means of multiple thresholds.

In [30], Shashua and Levin introduced a novel support vector machine to work on multiple thresholds. The author

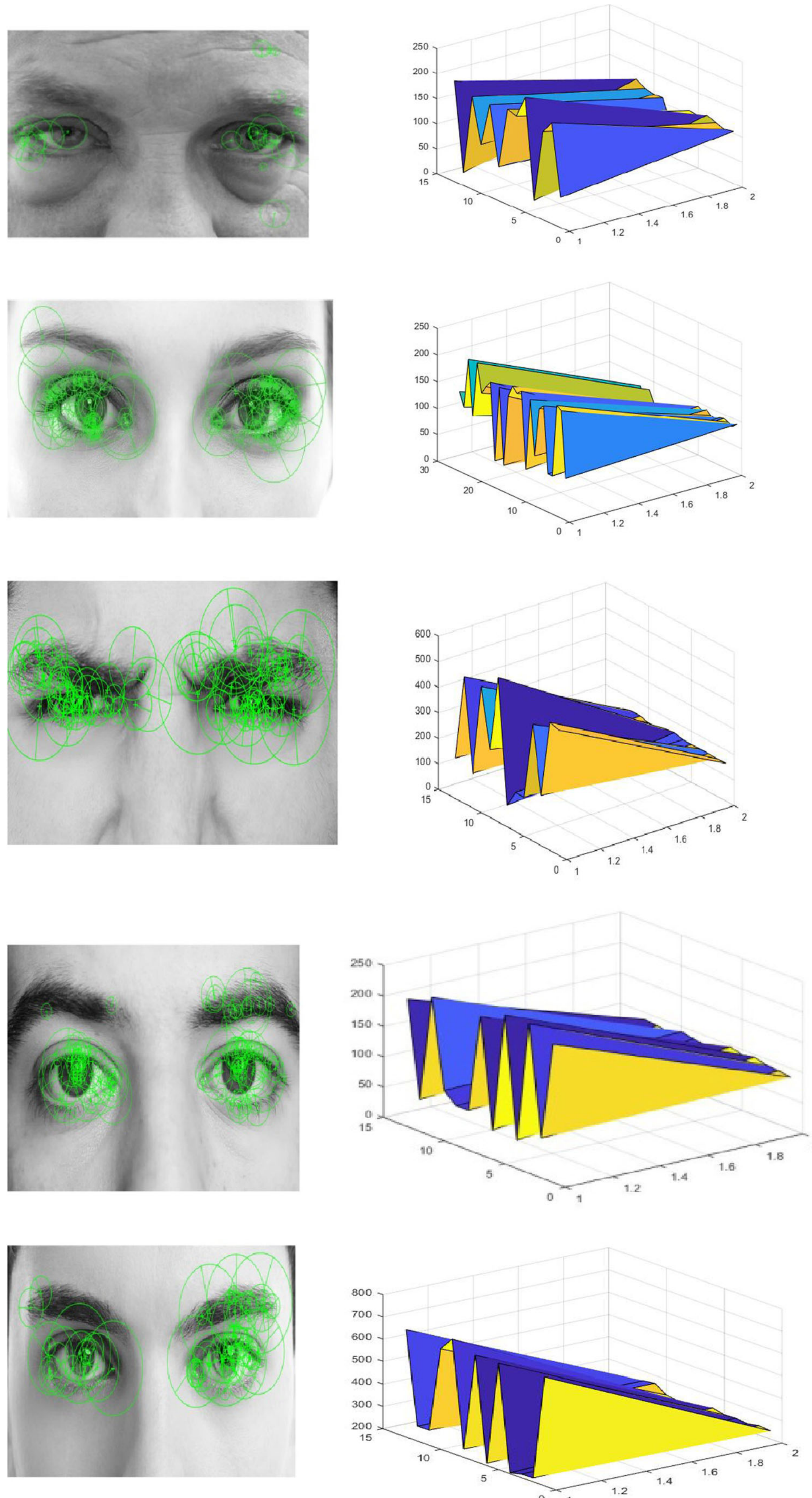


Fig. 2 Feature Extraction using SURF Algorithm

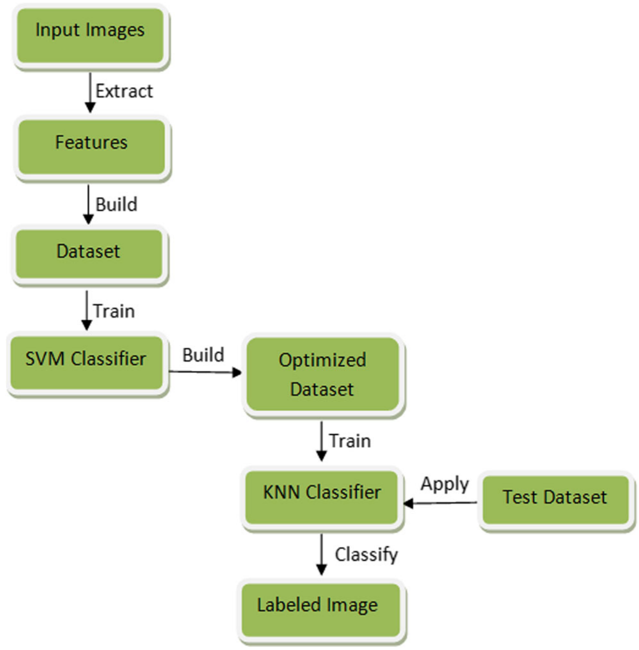


Fig. 3 Workflow of the Proposed System

even represented the complex ordinal regression problem in terms of simple binary classification sub-problems in order not to deviate from the direct utilization of well-known classification algorithms. For instance, a binary classifier is shaped by uniting several decision trees [31].

Recently, Li et al. [32] came up with a new framework to condense ordinal regression problem into a set of classification problems and further applied SVM to unravel the classification problems.

Proposed methodology

Feature detection using surf

SURF (Speeded Up Robust Features) [2] is a patented algorithm used mainly in image classification as well as registration, object recognition, or 3D reconstruction. SURF proved to be helpful in identifying similarities amid images as it extracts the key points from different regions of a given image.

SURF is utilized to identify and track people, objects and other points based on interest.

Working of SURF algorithm

Feature extraction For integral images, SURF employs square-shaped filters as an estimate of Gaussian Smoothing for faster filtering.

$$S(x,y) = \sum_{i=0}^{x} \sum_{j=0}^{y} I(i,j)$$

The sum of original image inside a rectangle can be estimated rapidly with integral image involving assessments at the four corners.

The algorithm utilizes a blob detector depending on Hessian matrix to calculate the points of interest. It uses the determinant for opting the scale, determining the local change around the points preferred wherever the determinant is maximal.

In an image I, given a point p = (x,y) and scale σ, the Hessian Matrix is

$$H(\rho,\sigma) = \left(L_{xx}\left(P,\sigma\right)\ L_{xy}(P,\sigma)\right.$$
$$\left.\left(L_{xx}\left(P,\sigma\right)\ L_{xy}(P,\sigma)\right)\right)$$

where $L_{xx}(P,\sigma)$ is the convolution of the second-order derivative of gaussian with the image I(x,y) at a point x.

The box filter of size 9 × 9 is an estimation of a Gaussian with σ = 1.2 and represents the utmost spatial resolution for blob-response maps.

Feature description Every individual key point is considered and its neighborhood regions are selected. Further, distinct feature descriptors are extracted from every region [4]. The feature descriptors [33] thus extracted are stored for image matching, face recognition, human tracing [34] etc. During process, the identified features must be distinct and free from

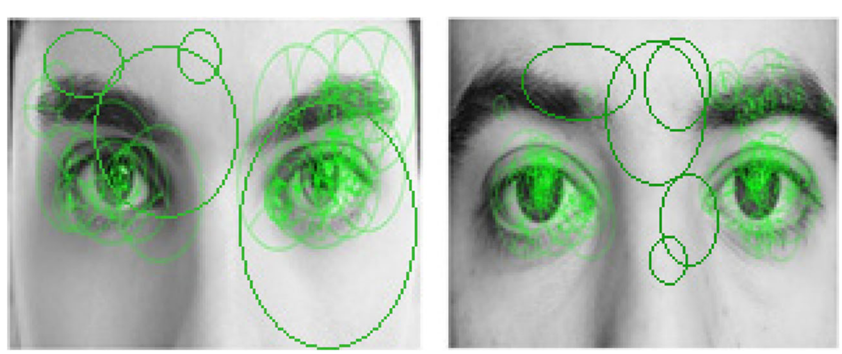


Fig. 4 Incorrect Features Extraction

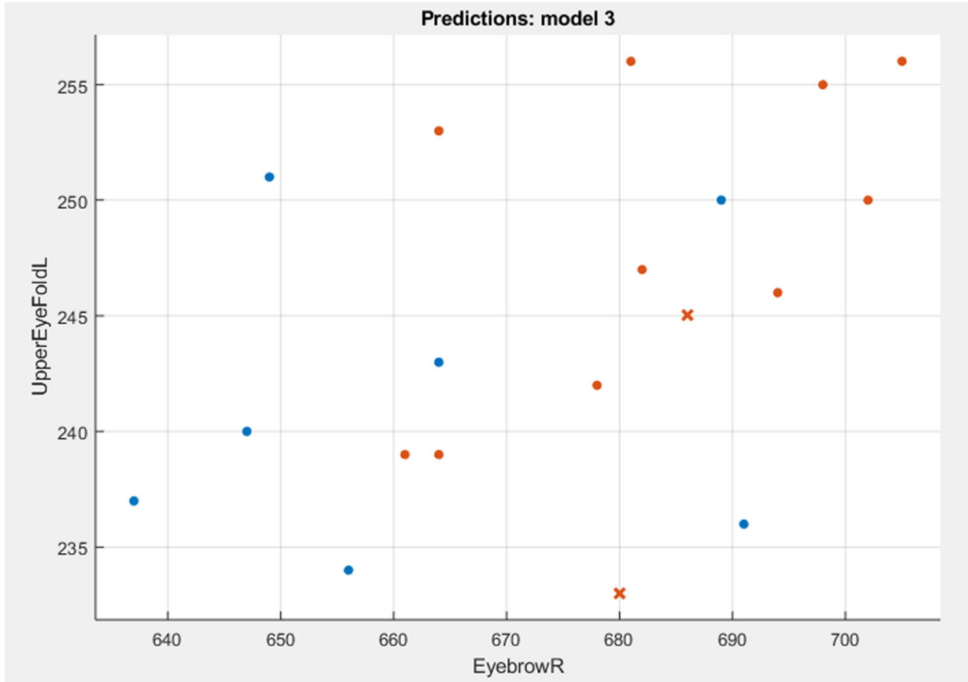


Fig. 5 Scatter Graph kNN Algorithm

noise and errors. These descriptors must provide consistent matching amid various viewpoints of the similar image.

Descriptor based on the sum of Haar wavelet responses

To describe the region around the point, a square region is extorted, centered on the point of interest and oriented along the orientation. The size of this window is 20s. The region of interest is divided into smaller 4×4 square sub-regions, and for all, the Haar wavelet responses [2] are haul out at 5×5 regularly spaced sample points. The responses are weighted with a Gaussian for added robustness for noise, deformations and translation.

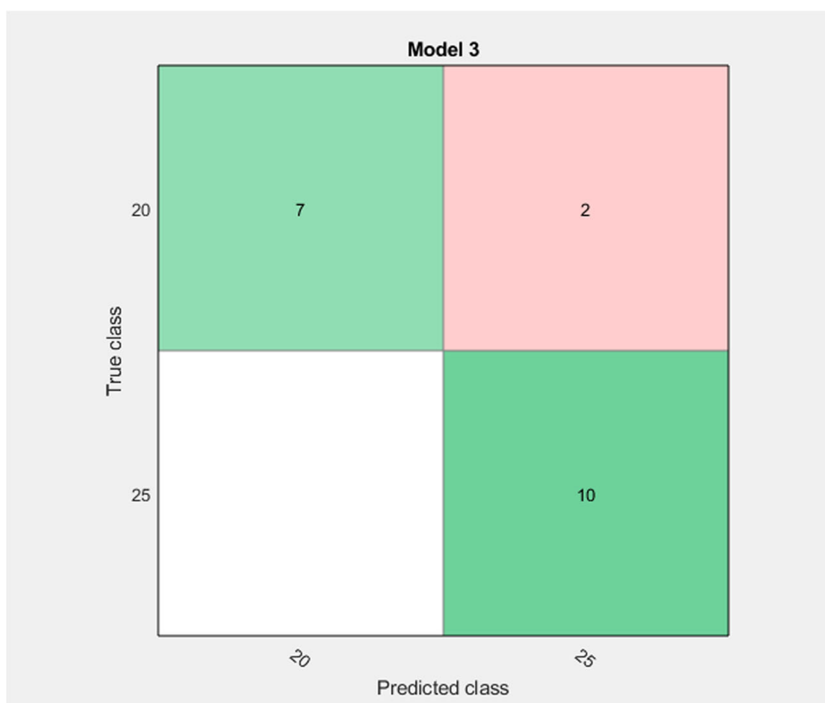


Fig. 6 Number of Observations kNN Algorithm

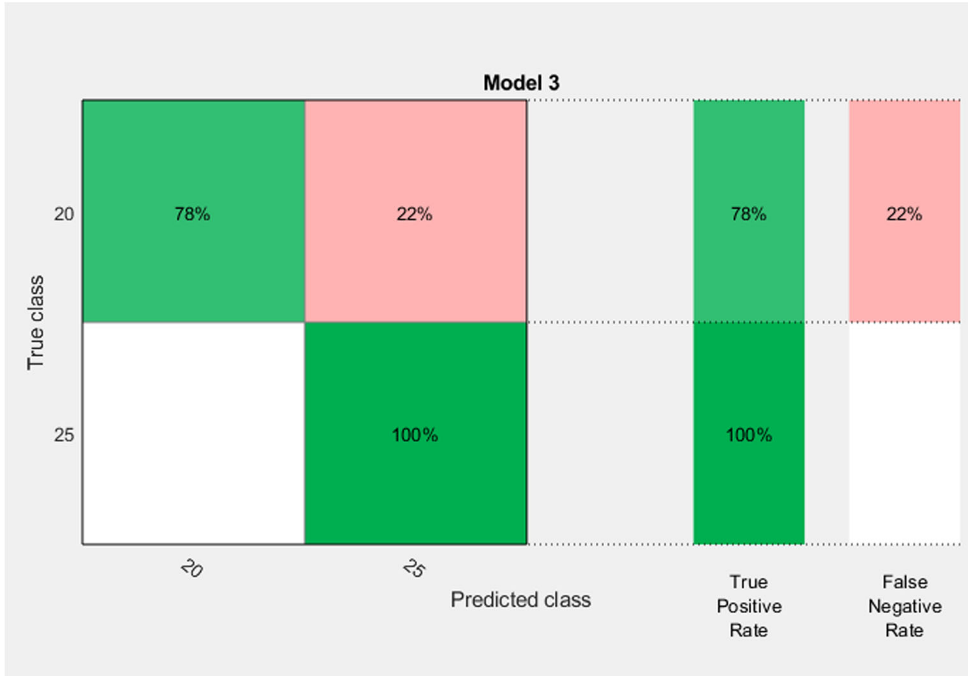


Fig. 7 True Positive rates and False Negative rates kNN Algorithm

Feature matching Feature descriptors of different images are compared and verified. Euclidean distance sare generally used by feature descriptor in matching images.

Periocular refers to the facial region in the vicinity of the eye, including eyelids, lashes and eyebrows. Periocular region is identified as the major trait to unconstrained biometrics which leads to the increasing demand for face and iris biometric systems [35, 36]. With surprisingly high discrimination ability, this region can be easily obtained with existing setups for face and iris, thus

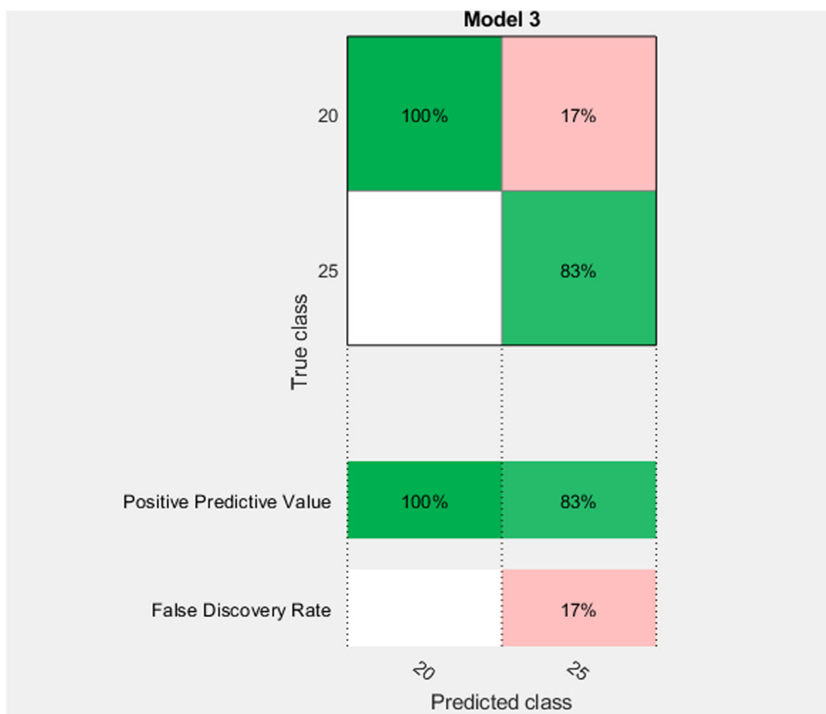


Fig. 8 Positive Predictive values kNN Algorithm

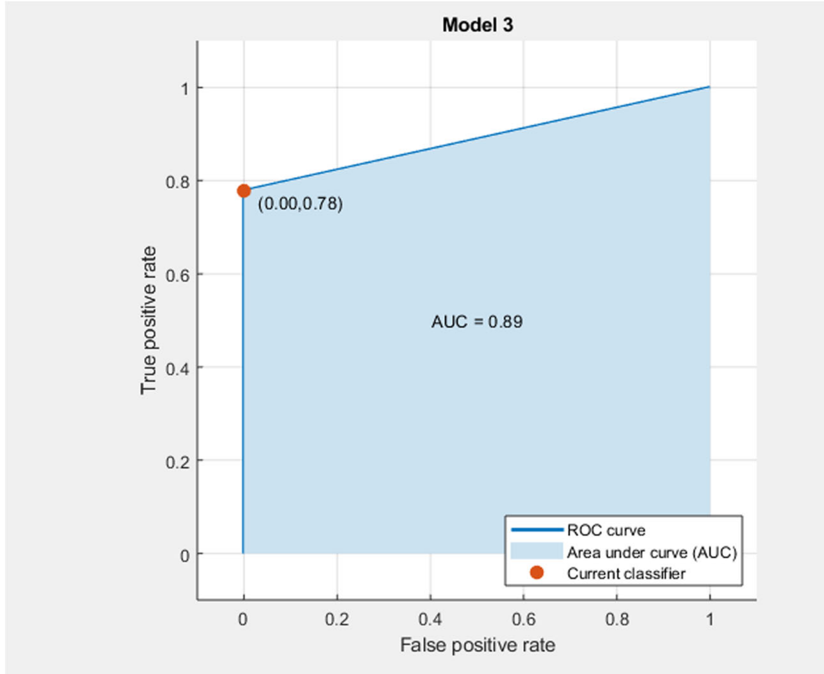


Fig. 9 kNN Algorithm NOC Curve Accuracy 89.5%

facilitating the interaction with biometric systems. Machine learning Techniques have become popular approaches to age recognition problems.

The periocular region features extracted using SURF algorithm includes both lower as well as upper eyelids, eye corners and eye folds, tear duct and eyebrow features of both eyes.

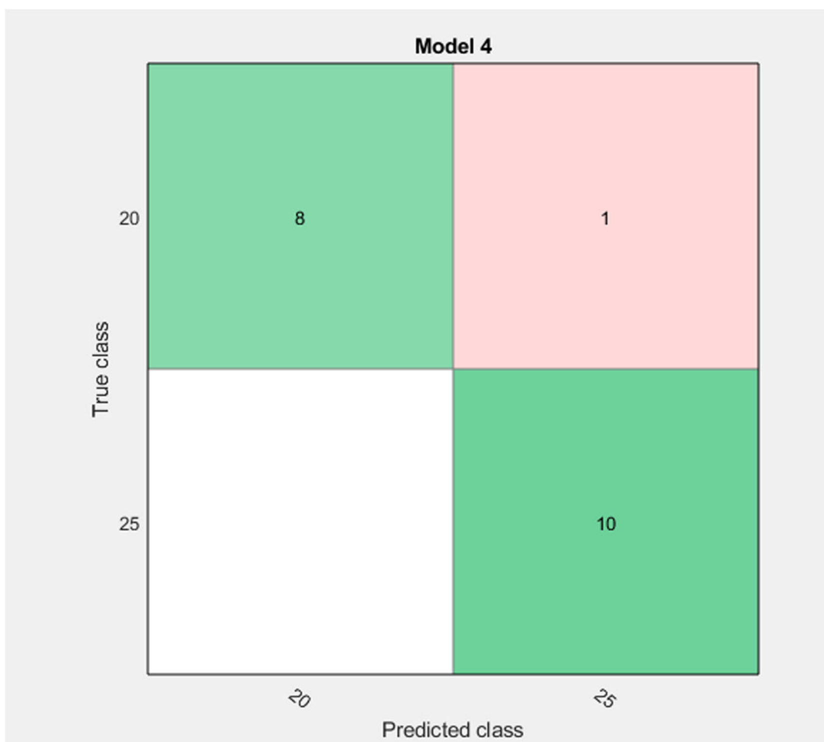


Fig. 10 Number of Observations SVM

Fig. 11 True Positive rates and False Negative rates for SVM

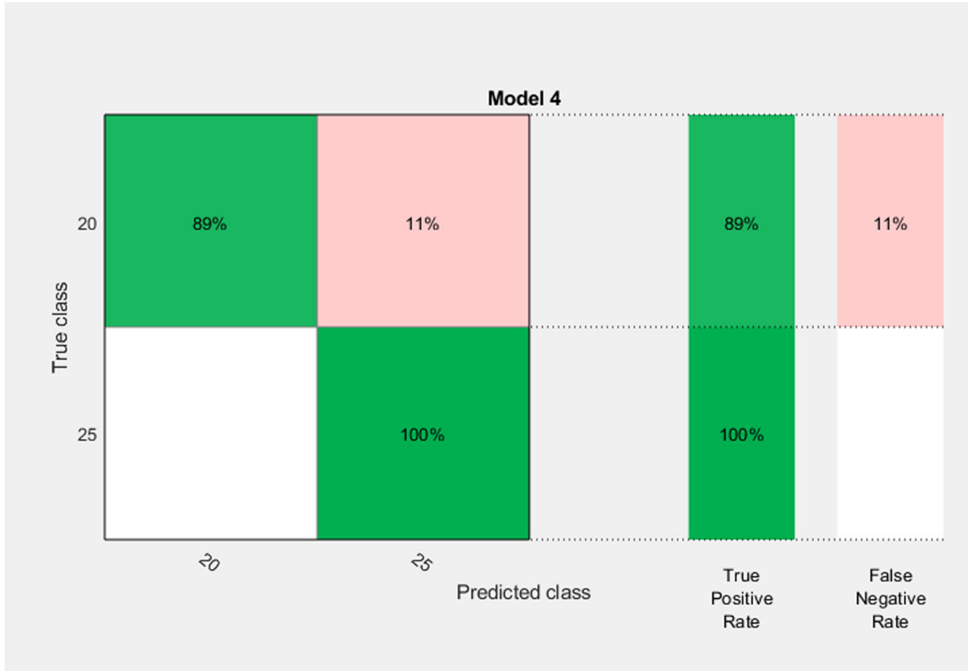
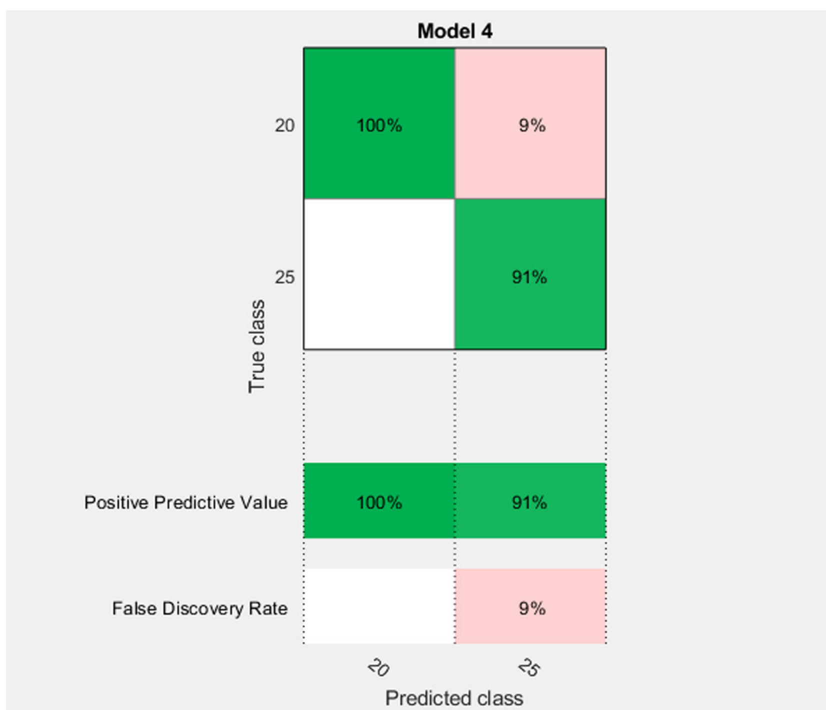


Fig. 12 Positive Predictive Values SVM



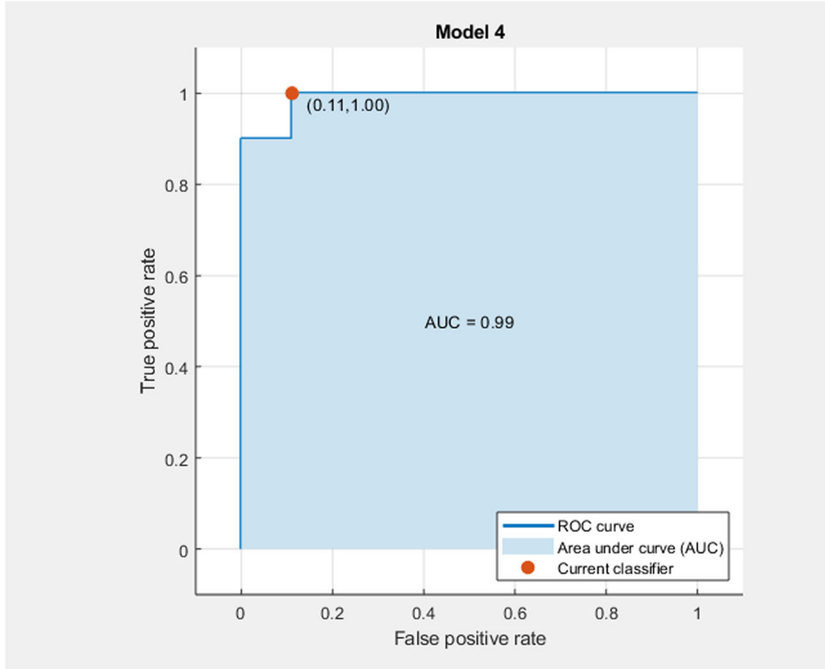


Fig. 13 NOC Curve Accuracy 94.7% SVM

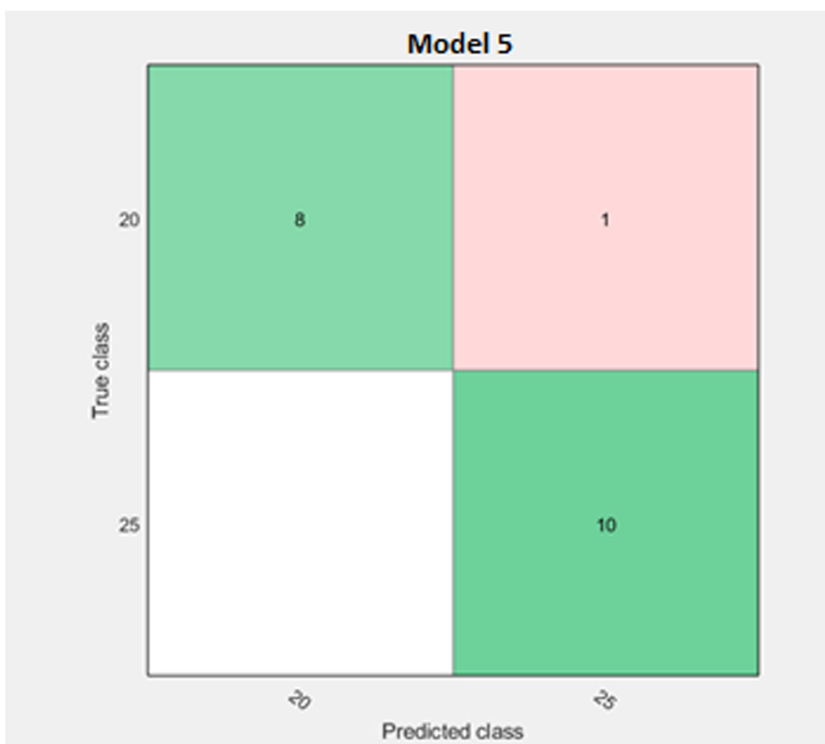


Fig. 14 Number of Observations kNN + SVM

Fig. 15 True Positive rates and False Negative rates for kNN + SVM

Fig. 16 Positive Predictive Values kNN + SVM

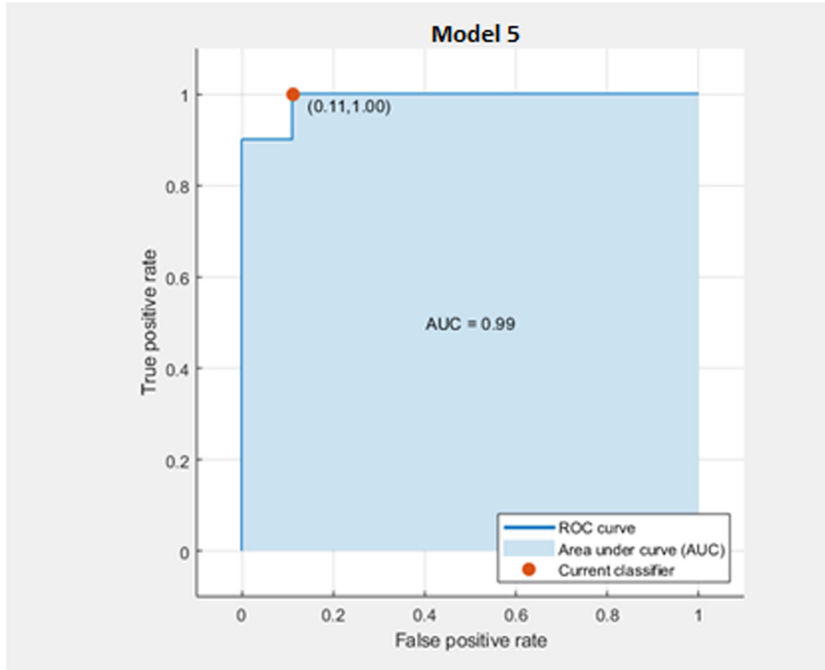


Fig. 17 NOC Curve Accuracy 96.5% kNN + SVM

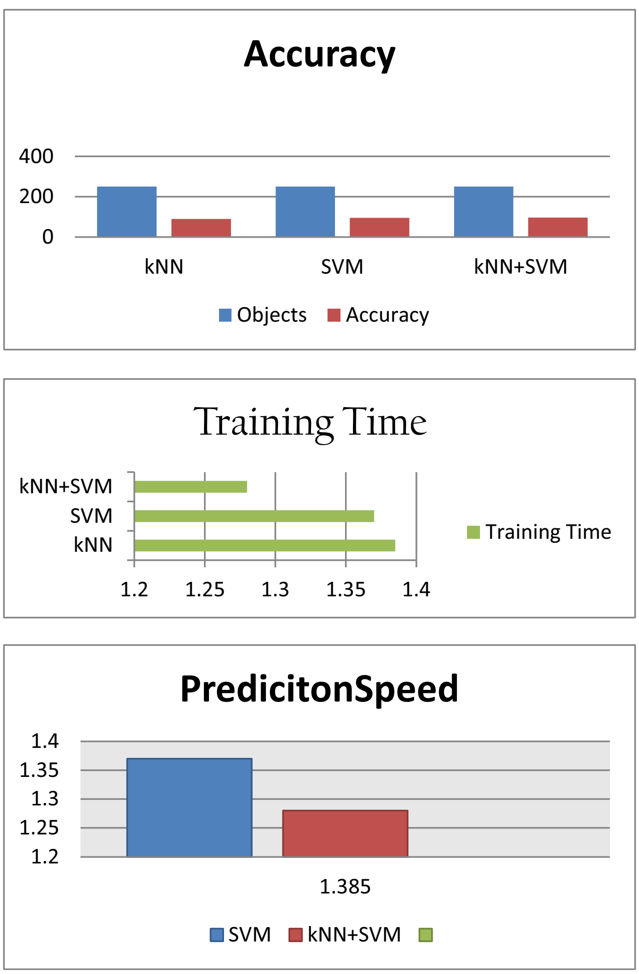


Fig. 18 Graph showing the performance of the proposed method for age estimation

(Figs. 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18 and 19).

AGE estimation using classification methods

Classification is a machine learning utility that assigns objects in a collection to target classes. The goal of classification is to predict the target class accurately for each object in the given dataset.

To perform object recognition accurately, a new Hybrid Classification method is proposed. The extracted features are provided to a new machine learning model, SVM-kNN in which SVM classifies the images based on these features into distinct categories resulting in an optimized dataset to train the kNN classifier. The new dataset of extracted features with

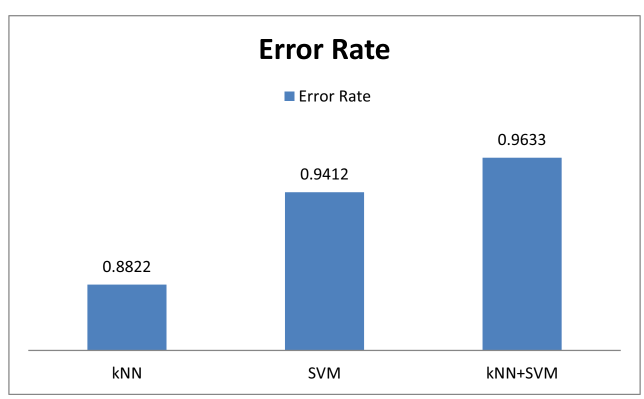


Fig. 19 Bar Graph Shows Error rate comparison

Table 1 Inconsistent dataset of Right Eye attributes before applying pre-processing technique

Eyebrow R	Upper Eye	UpperEyeFoldR	Below Eye	UpperEyeLidR	Side Eye	TearDuctR	InnerCornerR	LowerEyeLidR	OuterCornerR
637	0	662	0	665	0	645	653	678	689
689	0	675	2	653	23	688	679	681	658
664	0	686	210	643	5	684	656	640	682
691	0	689	0	680	1	682	657	652	695
656	0	697	0	697	0	654	678	660	659
686	0	687	0	654	0	672	679	649	693

label are then trained to kNN model successively applying the test data for further accurate estimation of person's age.

Support Vector Machine (SVM) is a statistical learning model that can be applied to continuous, binary, and categorical outcomes analogous to Gaussian, logistic and multinomial regression with a primary goal of prediction [16]. SVM is a mostly used method in pattern recognition and object recognition. The k-nearest neighbor's algorithm (k-NN) is a simplest and robust instant-based machine learning algorithm for classifying objects based on closest training examples in the feature space.

Proposed algorithm

1. *Given as input a dataset of 500 periocular region images of both eyes of different age groups 25,30,35…55,60 etc., for feature Extraction*
2. *Key Feature Points and vectors are extracted using SURF algorithm to build a training set*
3. *Features collected are formed as a set of tuples for each of the object to train the model.*
4. *The model is trained using SVM Classifier with the dataset built around the features to generate an optimized dataset to input it to the subsequent kNN classifier*
5. *The optimized dataset is trained to the kNN Classifier. It classifies the eye images as age group… the test dataset provided.*
6. *Accurate Age Detection as output*

Experimental results

The experiment is carried out in MATLAB computing environment. The dataset considered for training and test data set contains an adequate number of images to train and test the models to demonstrate the performance of new classifier SVM-kNN. Around 500 periocular region images were taken into account for both training and test datasets. Succinct

Table 2 Above Table Shows the consistent and relevant features after apply preprocessing technique

Eyebrow R	UpperEyeFoldR	UpperEyeLidR	TearDuctR	InnerCornerR	LowerEyeLidR	OuterCornerR	EyebrowL
637	662	665	645	653	678	689	230
689	675	653	688	679	681	658	233
664	686	643	684	656	640	682	228
691	689	680	682	657	652	695	253
656	697	697	654	678	660	659	226
686	687	654	672	679	649	693	246

Eyebrow R	UpperEyeFoldL	UpperEyeLidL	TearDuctL	InnerCornerL	LowerEyeLidL	OuterCornerL
637	237	236	233	233	226	246
689	250	239	230	255	228	234
664	243	237	248	251	225	240
691	236	224	256	235	242	228
656	234	242	234	225	251	231
686	245	236	238	230	247	244

Table 3 Sample Periocular Region Features Dataset

Eyebrow R	UpperEyeFoldR	UpperEyeLidR	TearDuctR	InnerCornerR	LowerEyeLidR	OuterCornerR	EyebrowL	UpperEyeFoldL
637	662	665	645	653	678	689	230	237
689	675	653	688	679	681	658	233	250
664	686	643	684	656	640	682	228	243
691	689	680	682	657	652	695	253	236
656	697	697	654	678	660	659	226	234
686	687	654	672	679	649	693	246	245
680	681	692	684	691	680	678	256	233
647	649	660	651	667	639	676	228	240
649	656	684	645	689	691	664	237	251
681	686	669	686	692	692	669	250	256
664	684	663	691	687	675	662	252	239
682	699	663	700	683	668	679	255	247
702	705	673	677	666	705	679	242	250
694	701	659	696	671	701	665	256	246
664	685	671	698	699	660	670	245	253
661	690	665	663	688	680	686	241	239
698	661	704	686	668	674	663	246	255
678	701	680	705	689	678	686	241	242
705	679	691	660	698	693	675	240	256

Eyebrow R	UpperEyeLidL	TearDuctL	InnerCornerL	LowerEyeLidL	OuterCornerL	Age
637	236	233	233	226	246	20
689	239	230	255	228	234	20
664	237	248	251	225	240	20
691	224	256	235	242	228	20
656	242	234	225	251	231	20
686	236	238	230	247	244	20
680	241	249	234	231	242	20
647	225	240	255	243	255	20
649	233	234	249	233	242	20
681	247	255	247	251	255	25
664	256	253	239	251	242	25
682	247	238	240	251	240	25
702	247	252	255	242	250	25
694	242	242	247	253	249	25
664	238	255	240	245	246	25
661	256	254	247	252	250	25
698	250	249	247	256	253	25
678	248	250	248	240	246	25
705	246	243	239	244	238	25

Table 4 KNN Algorithm Performance in Object Detection

Algorithm	Accuracy	Prediction Speed	Training Time
kNN	89.5%	370 obs/s	1.3835 s

Table 5 SVM Algorithm Performance in Object Detection

Algorithm	Accuracy	Prediction Speed	Training Time
SVM	94.7%	500 obs/s	1.37 s

Table 6 SVM Algorithm Performance in Object Detection

Algorithm	Accuracy	Prediction Speed	Training Time
kNN + SVM	96.7%	635 obs/s	1.28 s

Table 7 Shows the performance of new classifier compared to traditional classifiers

Algorithm	Training Time in ms	Prediction speed objects/s	Correctly Classified Objects per 250 records	Accuracy
kNN	1.385	370	223	89.5
SVM	1.37	500	235	94.7
kNN + SVM	1.28	635	241	96.5

Table 8 Error Rate of each of the algorithm considered

Algorithm	Error Rate
kNN	0.8822
SVM	0.9412
kNN + SVM	0.9633

description of dataset considered in this research is presented below with features extracted. (Tables 1, 2, 3, 4, 5, 6, 7 and 8)

The graph shown above depicts that the proposed method outperforms the single SVM and kNN. The proposed method performs accurately in terms of speed, time and accuracy in determining the age of a specific person using periocular features.

Error rate calculation The "true" error rate can be obtained by the comparison of the observed values of Y and the prediction of the classifier M on the whole population.

$$\varepsilon = \frac{\sum_{\omega \epsilon \Omega_{pop}} [Y(\omega]) \neq Y^{-}(\omega)}{card(\Omega_{pop})}$$

Error rate computed on the entire population = probability of misclassification of the classifier.

Conclusion

The result for each algorithm is quite satisfying with the accuracy of 89.5% for kNN, 94.7% for SVM and 96.57% accuracy for SVM-kNN. From experimental results, it is clear that merging SVM and kNN with SURF feature detection algorithm can produce better results. Our new proposed method is compared with traditional machine learning classifiers SVM and kNN and proven to be most appropriate for age recognition in terms of speed, time and classification accuracy.

Compliance with ethical standards

Conflict of interest Kamarajugadda Kishore Kumar declares that he/she has no conflict of interest. Polipalli Trinatha Rao declares that he/she has no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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