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Ethnicity Classification: Discriminating Between Iranian and Asian Populations Using Hybrid Deep Learning Algorithm

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Abstract: The rapid advancement of deep learning techniques has opened new avenues for solving complex classification problems in various domains. This research explores the application of Convolutional Neural Networks (CNN), specifically the VGG16 architecture, in conjunction with Support Vector Machines (SVM) for the classification of ethnicity using Iranian and Asian facial images. The classification of ethnicity based on facial features is a challenging task due to the subtle and complex variations within and between different ethnic groups. The proposed methodology involves a two-step process. First, the VGG16 CNN model is utilized to extract high-level features from the facial images. The pre-trained VGG16 model, known for its depth and representational power, is fine-tuned on the dataset to capture relevant ethnic features. The extracted features are then fed into an SVM classifier, which is trained to distinguish between Iranian and Asian facial characteristics. A comprehensive dataset consisting of labeled Iranian and Asian facial images is compiled and preprocessed for training and evaluation. The model's performance is assessed using metrics such as accuracy. Various experiments are conducted to optimize hyperparameters and validate the generalization capability of the proposed model. Additionally, visualization techniques are employed to provide insights into the features learned by the CNN and the decision boundaries established by the SVM. The results indicate that the combined approach of CNN-VGG16 and SVM yields promising accuracy in the classification of ethnicity based on facial images.

Keywords: Convolutional Neural Networks, Support Vector Machines, Artificial Neural Networks, Visual Geometric Group.

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1. INTRODUCTION

The identification of a person's ethnicity from a facial image is a complex process. A person's face contains a multitude of information, such as identity, age, gender, expression, and race. Of these, race is particularly important because it remains constant throughout a person's lifetime and can greatly aid in the accuracy of facial recognition systems. As a result, there has been a growing interest in automatic facial ethnicity classification in recent years, and numerous methods have been proposed. However, accurately, and quickly classifying different races based on facial images in an uncontrolled environment poses a significant challenge. To achieve efficient classification, race-sensitive features must be identified from facial images. These discriminative features can be categorized into three groups: chromatic/skin tone, local features, and global features. Skin tone alone cannot be used to classify different races due to the similar skin color of different ethnicities and the extreme variation in illumination conditions in real-world scenarios. However, when combined with local or global descriptors, classification accuracy can be significantly improved.

Race classification has been historically used for various practical purposes, but it's important to note that it has also been associated with discrimination, prejudice, and harm. Many experts and organizations now advocate for more careful and ethical approaches to understanding human diversity. Nevertheless, there are many practical applications of race classification such as healthcare and medical research, public health, census and demographics, education, law enforcement, diversity and inclusion initiatives, cultural preservation, historical research, marketing and consumer research, and social services [1].

Releated Work

In recent years, there has been a significant surge in research employing computer vision and deep learning algorithms for race and gender classification. Noteworthy contributions include research endeavors such as the study introduced for the recognition of semantic facial features through deep learning [2]. Additionally, Haoxuan Chen et al. executed various methodologies, including a K-nearest neighbor algorithm, a Support Vector Machine (SVM) classifier, a two-layer neural network, and a Convolutional Neural Network (CNN), to train a classifier for predicting Chinese, Japanese, and Korean ethnicities [3]. This collective effort resulted in an impressive overall prediction accuracy of 89.2% in the three-class classification task. Furthermore, other researchers have delved into ethnicity classification utilizing the CIFAR-10 network, focusing on distinctions between categories such as black and white individuals, Chinese and non- Chinese [4].

Another scholarly paper focused on the comparative analysis of various machine learning and deep learning algorithms for ethnicity classification. Specifically, the study evaluated the performance of Support Vector Machines (SVM), Random Forest, Artificial Neural Networks (ANN), Transfer Learning, and Convolutional Neural Networks (CNNs) in the context of age, gender, and ethnicity classification. The research's conclusive findings indicated that CNNs consistently yielded the most favorable results across all three classification tasks [5]. In a related vein, Greco et al. adopted a distinctive approach to the challenge of ethnicity

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classification. Rather than proposing a novel ethnicity classification algorithm, they contributed a novel dataset expressly designed for ethnicity classification purposes [6].

Furthermore, some researchers introduced a face segmentation algorithm capable of partitioning a given facial image into seven distinct facial classes. Building upon the insights gained from this face segmentation model, they devised an innovative ethnicity classification algorithm. Their methodology entailed the utilization of a Deep Convolutional Neural Network (DCNN) to construct the face segmentation model. To train the DCNN effectively, facial images were meticulously annotated according to seven distinct categories, encompassing nose, skin, hair, eyes, eyebrows, background, and mouth [7]. Table (1) provides an overview of recent studies in the field of ethnicity classification.

In the present research, a novel hybrid classification method has been introduced for the differentiation between the Iranian and Asian racial groups. This innovative approach employs two distinct data sets the first one for Iranian (IFD) and the second one for Asian (UTKface). The sections of the paper adhere to a structured format as follows; the first one is introduction which provides an introductory overview of the subject matter.

Table (1) Overview of Recent Studies on Ethnicity classification

Study	Classifier	Dataset	Contained	Accuracy
2004[8]	LDA	Yale and AR	Asian & non-Asian	96.3%
2004[9]	SVM	Private+ HOIP	Asian-European, African	94%
2010[10]	SVM	FERET and PEAL	ALL	94-98%
2010[11]	SVM	500 images	Caucasian, Asian and African American	95%
2010[12]	SVM	FRGC	Asian &non-Asian	93%
2012[13]	Min. distance	FERET	All	95%
2012[14]	KCFA	Private	All	96%
2014[15]	CCA	Dataset,55000 image	Asian- Indian	91.5%
2015[16]	HCP-CNN	PASCAL(VOC)	All	91%
2016[17]	DNN	public	All	99.44%
2016[18]	DCNN	MORPH-II, CASIA-PEAL, CASIA-WebFace.	All	93.5%
2018[19]	DCNN, VGG	JAFFE, CUFS, FEI	Japanese, Chinese, Brazilian	88.6%
2019[20]	SVM	FERET	Black, white, Asian	93.7%
2018[21]	CNN	FERET	All	98.3%
2019[22]	CNN	Asian and non- Asian	Asian &non-Asian	84.2%
2019[23]	CNN	LFW	gender	98.4%

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Study	Classifier	Dataset	Contained	Accuracy
2021[24]	CNN	Private	Arab	54.3%

The paper is organized into distinct sections to facilitate a structured exploration of the research topic. In the second part, we undertake a comprehensive review of pertinent literature and related research, providing essential context for our study. Subsequently, in the third section, we offer a comprehensive explanation of the proposed hybrid system, which encompasses Convolutional Neural Networks (CNNs), with a particular focus on the VGG16 architecture—a key component of our approach. Following this, we delve into an in-depth exploration of the Support Vector Machine (SVM) algorithm, elucidating its role and contribution within our methodology. Moving forward, the fourth section presents the results stemming from our experimentation, allowing for an insightful examination of the system's performance. Moreover, we conduct a meticulous comparative analysis in this section, contrasting our results with those of previous research efforts to assess the significance of our contributions. Finally, the paper reaches its conclusion in the last section, summarizing key findings and providing concluding remarks that encapsulate the overall research endeavor.

Proposed Hybrid System (CNN-Vgg16 with SVM)
Figure (1) provides an overview of the proposed hybrid deep learning system designed for ethnicity classification.

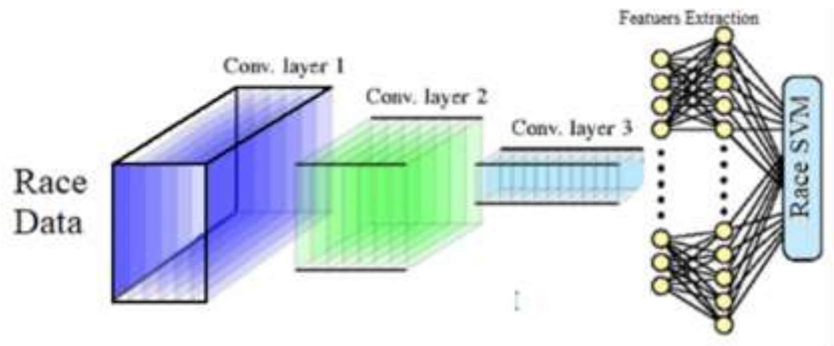

Fig. (1) Proposed Model for Race Classification

Figure 1 offers a comprehensive overview of the proposed hybrid deep learning system tailored for ethnicity classification. In this system, a Convolutional Neural Network (CNN), specifically the VGG16 architecture, is employed to extract pertinent image features. These extracted features are subsequently fed into an SVM classifier, facilitating the distinction between individuals of Iranian and Asian ethnic backgrounds.

3.1 Convolution Neural Network (VGG-16)
Image feature extraction is a crucial step in building an image classification system. It involves extracting meaningful and representative features from images that can be used to distinguish between different classes or categories. Feature extraction from face images involves extracting discriminative facial features that can be used for ethnicity classification. CNNs are widely favored for image classification due to their exceptional ability to automatically learn

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hierarchical representations, making them a suitable and effective approach for the current project. The process begins with an input image, which is typically represented as a grid of pixels. After that the image is passed through one or more convolutional layers. Each convolutional layer consists of multiple learnable filters or kernels. These filters perform a convolution operation on the image, which involves sliding the filters across the input image and computing dot products between the filter weights and local image patches. The resulting output is called a feature map or activation map. Figure (2) shows architecture of VGG16 which is utilization of 16 convolutional layers, which are structured based on 3x3 modules [25]. In each layer, the output characteristics are dependent on specific regions of the original image: a 3x3 region in the first layer, a 5x5 region in the second layer, a 7x7 region in the third layer, reducing volume size is handled by max pooling. Two fully connected layers, each with 4,096 nodes are then followed by a SoftMax classifier. This architecture takes as input a 224-by-224-by-3 image.

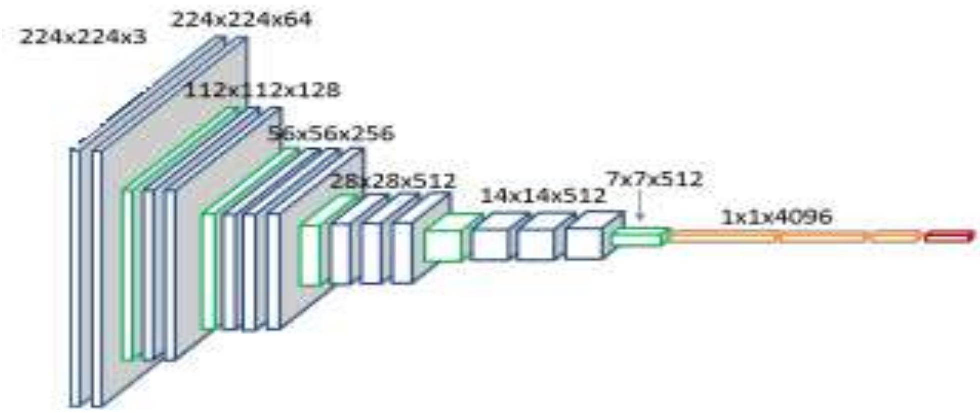

Fig (2) The architecture of the VggNet-16 models[26]

3.2 Support Vector Machine (SVM)

SVM, or Support Vector Machine as shown in Figure (3), is a widely used binary classifier in various pattern classification applications. It has also found success in fields such as bioinformatics, face detection and recognition, object detection and recognition, handwriting recognition, information and image retrieval, and speaker and speech verification. One of the key strengths of SVM is its ability to generalize well. This is due to its foundation in the Structural Risk Minimization (SRM) principle, which is rooted in statistical learning theory. In supervised learning, SVM is trained using input data that is labeled with different classes [27]. The goal of SVM is to find a hyperplane, as defined by (1) below, that maximally separates the two classes labeled with:

$$F(x)=\sum_{i=1}^{n} w_i x_i + b\text{-------}(1)$$

Here, 'w' represents the weights assigned to the input features, 'x' represents the input data, and 'b' is a bias term. The margin refers to the distance between the two lines that pass through the data points closest to the opposite class. These data points, known as Support Vectors (SV), play a crucial role in defining the decision boundary. By maximizing the margin, SVM aims to achieve a clear separation between the classes, leading to improved generalization and

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robustness of the model. This ability to find an optimal decision boundary makes SVM particularly effective in dealing with both linearly and non-linearly separable data.
In summary, SVM is a powerful binary classifier that applies the SRM principle to find a hyperplane that maximizes the margin between classes. It has demonstrated success in various fields and is valued for its generalization properties and ability to handle diverse data types. The line passing through the SV have equations w_i+b≥1 for class +1 and w+x_i≤-1 for class -1.

$$w.x_1 + b = 1 ------ (2)$$
$$w.x_2 + b = -1 ----(3)$$
$$w.(x_1 - x_2) = 2$$
$$\frac{w}{\|w\|}.(x_1 - x_2) = \frac{2}{\|w\|} ----(4)$$
$$y_i(w.x_i + b) \geq 1 --- (5)$$

Maximum margin can be found by minimizing (5). This forms a Quadratic Programming (QP) problem. World data is usually not separable by the linear classifier. For this reason, non-linear kernel functions are used to map data from input space to a higher dimensional space where data can be linear separable.

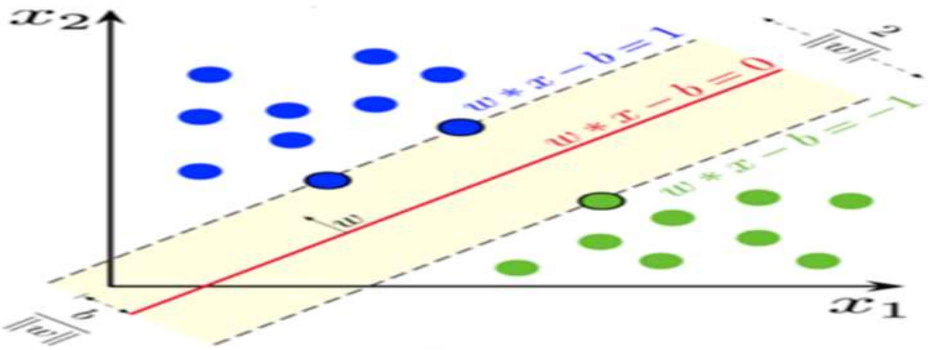

Fig. (3) Support Vector Machine (SVM)

The proposed hybrid system for ethnicity classification, could be represented mathematically and characterization of the training process by the following steps:

Data Preparation: As mentioned before, we have a dataset of face images with corresponding race labels.

$$D = \{(x_i, y_i)\}_{i=1}^{N} ----(6)$$

Where x_i represents the i-th face image and y_i is the ethnicity label.

Convolutional Neural Network: The CNN is used to extract deep features from the face images. Let's denote the CNN as F_{CNN} and its output after feature extraction as:

$$Z = \{(z_i)\}_{i=1}^{N} ----- (7)$$

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Were z_i represents the extracted features for the i-th face image. The CNN can be represented as:

$$Z = F_{CNN}(X) \text{---------} (8)$$

Support Vector Machine (SVM) Classifier: The SVM classifier is trained on the extracted features Z and their corresponding race labels Y. Let's denote the SVM function as F_{SVM}, and the SVM classifier is trained to find the decision boundary that separates different races. The SVM function can be represented as:

$$F_{SVM}(Z_i) = \text{argmax}_y\big((W + Z_i) + b\big) ------(9)$$

Where w and b are the weight vector and bias term of the SVM, respectively.

Hybrid Classification: For a new face image new, Xnew, we pass it through the CNN to extract its features

$$Z_{new} = F_{CNN}(X_{new}) ----- (10)$$

Then, we use the SVM classifier to predict the race label using the extracted features:

$$y_{pred} = F_{SVM}(Z_{new}) ----- (11)$$

2. EXPERIMENTS AND RESULTS

In this project, we propose a methodology centered around deep learning-based feature extraction, which is employed to train a classifier capable of discerning ethnicity as demonstrated in the figure (1). The classification system presented in this study uses a method where a separately pre-trained convolutional neural network (CNN) acts as a deep feature extractor, together with an SVM classifier. Specifically, the VggNet-16 model was pre-trained to act as a deep feature extractor and SVM classifier.the study employs two separate datasets: one comprising Asian facial images (UTKface) and another containing Iranian facial images (IFD). Figure (4) presents a collection of sample face images from these utilized datasets.

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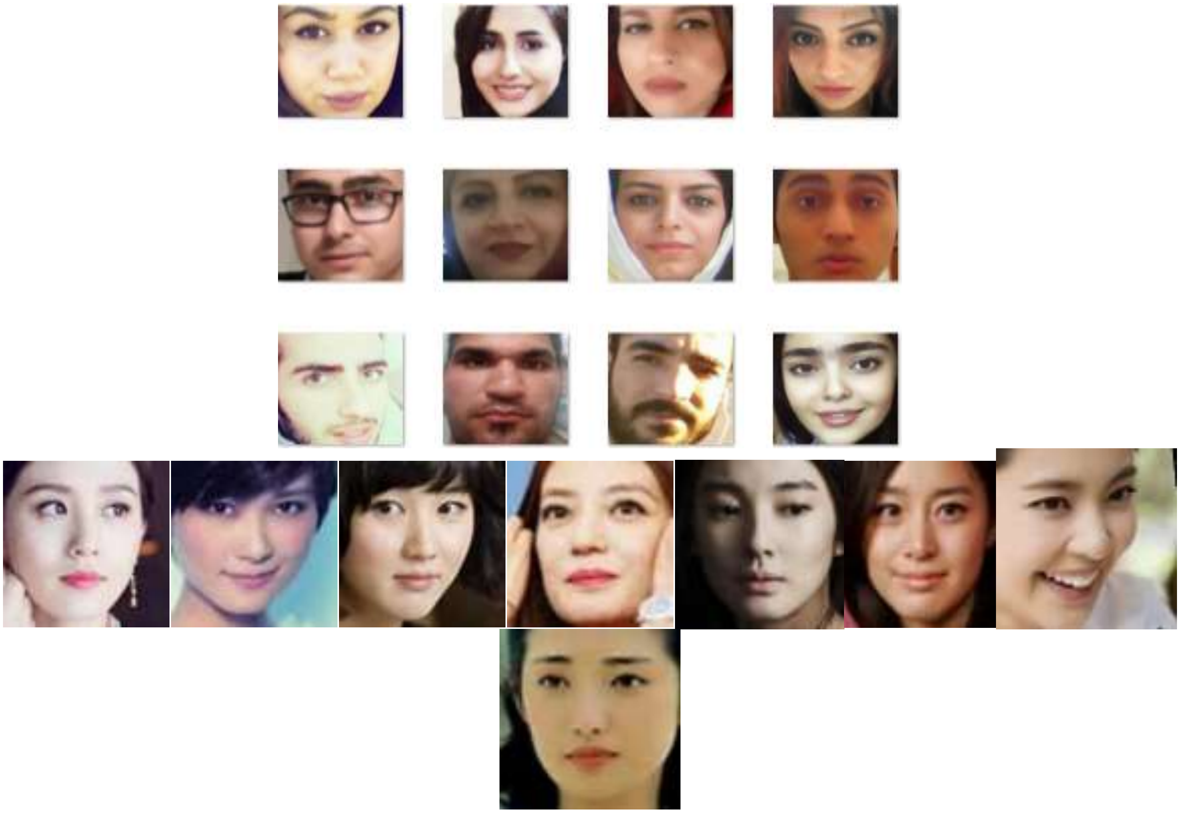

Fig (4) Sample Face Images from These Utilized Datasets

To classify between Iranians and Asians using VGG16 and SVM, we utilized two sets of images - the first set for Iranians (IFD) and the second for Asians (UTKface). The process began by preparing and cleaning the data, where each set of images was divided into training and testing subsets. The images were resized to a consistent size, such as 224x224 pixels, to match the requirements of the VGG16 model. we employed the pre-trained VGG16 model, initially designed for ImageNet, and removed its last fully connected layer. The majority of the model's layers were frozen, except for the final layers. Feature extraction was then performed by passing the training images through the modified VGG16 model, and the extracted features were saved in separate files. Subsequently, I configured a Support Vector Machine (SVM) using libraries like Scikit-learn in MATLAB. The extracted features from the training set and appropriate labels (Iranian or Asian) were used to train the SVM model.Two types of datasets were utilized. The first dataset comprises images representing the Iranian ethnicity, while the second one encompasses various ethnicities, including the Asian ethnicity. As for the first dataset, as previously mentioned, it was acquired from Kaggle, a publicly available dataset consisting of approximately 4,000 images. Table (2) succinctly encapsulates the information pertaining to each dataset utilized in the current research.

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Table (2) Details of Datasets

Dataset	**Dataset Description**			
	Total Images	Used for	Size	Type
IFD	4309	Ethnicity/Gender	200*200	JPEG
UTKface	16348	Ethnicity/Gender	200*200	JPEG

In the context of ethnicity classification using discrete Iranian and Asian facial datasets, the initial phase encompasses image preprocessing and enhancement to ensure uniform input standards. Achieving this involves the normalization of images to a consistent size and format. After this preprocessing, dataset segmentation involves creating a training subset (comprising 80% of the data) alongside a testing subset (constituting 20%) to facilitate the extraction of pertinent features. Employing the VGG16 model, features are extracted by retaining feature-rich layers such as "fc7" while discarding classification layers. The subsequent phase involves the training of a Support Vector Machine (SVM) classifier. This classifier is educated using extracted features from both the Iranian and Asian training datasets, allowing it to proficiently discern and differentiate between the distinctive ethnicities under consideration. Figure (5) illustrates the utilization of a bifurcated ethnicity distribution for the purpose of training a model designed to classify ethnicities.

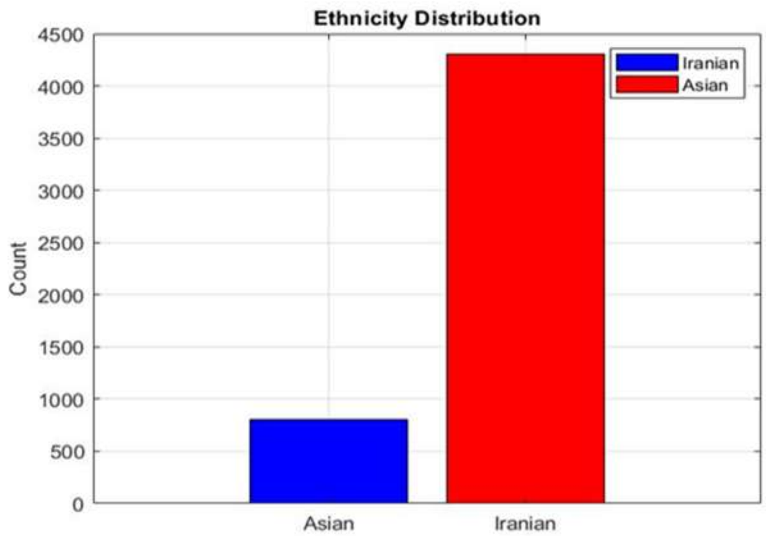

Fig (5) Race Distribution

The distribution encompasses two distinct labels that serve as representative categories within the context of the model's classification task.
The aim of this approach is to enhance the model's capacity to accurately classify and differentiate between various ethnicities based on the training data provided. By employing a two-label ethnicity distribution for training, the model is poised to develop a nuanced understanding of the distinctions between the specified ethnic groups, thereby facilitating its ability to make informed and precise classifications in real-world applications. Figures (6) and (7) present the results of the SVM classifier's accuracy and SVM validation accuracy,

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respectively. These visualizations offer insights into the performance of the Support Vector Machine (SVM) model in terms of its classification accuracy and generalization capabilities.

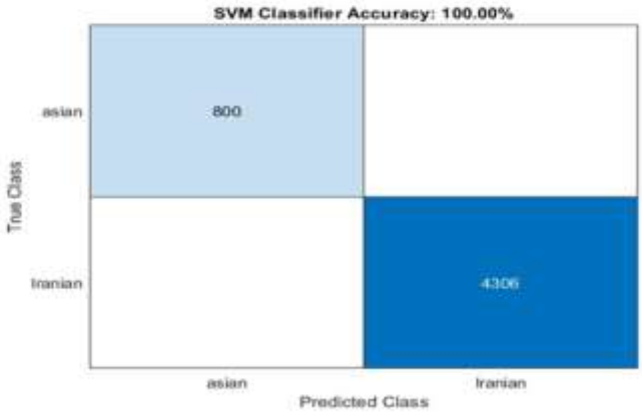

Fig (6) SVM Classifier Accuracy

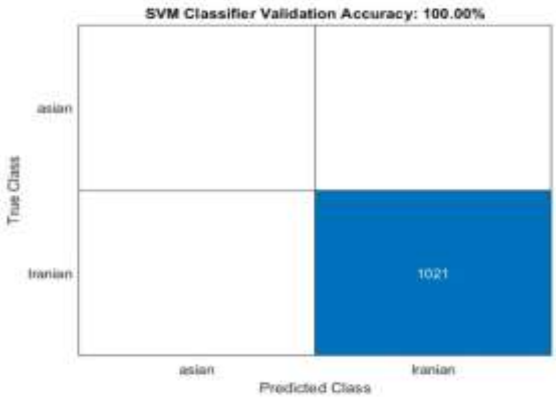

Fig (7) SVM Classifier Validation Accuracy

Figure graphically portrays the performance assessment of a Support Vector Machine (SVM) classifier. The x-axis of this graph corresponds to the predicted classes assigned by the SVM model, while the y-axis represents the true classes of the instances in the dataset. In this visual representation, each data point symbolizes an individual instance, and its position on the graph reflects the comparison between the classifier's prediction and the actual class. The main diagonal line from the bottom-left corner to the top-right corner represents perfect predictions, where the predicted class aligns with the true class. The deviations from this diagonal line reveal instances where the classifier's predictions diverge from reality. Points above the diagonal indicate cases where the SVM assigned a higher-class label than the true class, while points below the diagonal signify the opposite scenario. Figure (8) shows the accuracy for ethnicity classification for Asian and Iranian dataset. the accuracy of the VGG16 model for the ethnicity dataset reached an even higher value of 96.85%.

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Fig (8) Accuracy of Ethnicity classification for (Asian & Iranian) Dataset

Figure (9) shows accuracy of Vgg16 and SVN classifier whereas figure (10) demonstrates the performance of the model in classifying ethnicity for both Asian and Iranian datasets. The model achieved a training accuracy of 0.967 and a testing accuracy of 0.945. In terms of loss, the training loss was 0.2, while the testing loss was 0.3.

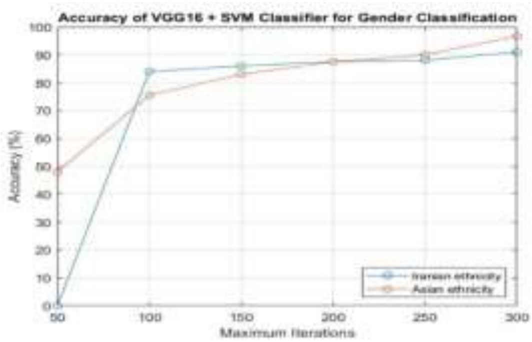

Fig (9) Accuracy of Vgg16 and SVM for Ethnicity Classification

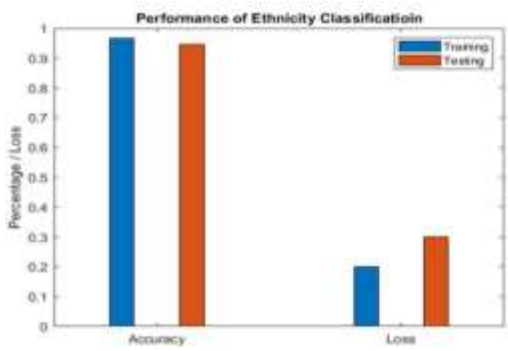

Fig (10) Performance for Ethnicity Classification

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Table (3) presents a comparative analysis of the current study against prior state-of-the-art research, providing insights into the advancements and contributions of the undertaken research.

Table (3) Comparative Analysis of the Current Study with another Research

References	Techniques	Dataset	Accuracy
[28]	CNN	MORPH	69%
[29]	Deep Neural Network	FERET	70%
[30]	CNN	MORPH	71.3%
[31]	CNN	MORPH	70.89%
Proposed Model	CNN(Vgg16) +SVM	IFD and UTKFace	96%

3. CONCLUSION

Within this paper, we have introduced a novel approach to ethnicity classification, specifically targeting the Iranian and Asian races, leveraging a hybrid deep learning system. Our methodology has been rigorously assessed using two distinct datasets: the IFD dataset for Iranians and the UTK face dataset for Asians. The crux of our approach revolves around harnessing the robust capabilities of the VGG16 neural network architecture to extract salient image features, which are subsequently fed into an SVM classifier. Our findings reveal a notable enhancement in classification accuracy when compared to other prevailing state-of-the-art methods. This outcome underscores the efficacy and potential of our proposed approach in effectively addressing the challenging task of ethnicity classification.

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