2024, 21(12 Suppl.): 4146-4162
https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

Predicting Movie Production Years through Facial Recognition of Actors with Machine Learning

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Received 25/04/2023, Revised 19/01/2024, Accepted 21/01/2024, Published Online First 20/06/2024, Published 22/12/2024

Abstract

This study used machine learning algorithms to identify actors and extract the age of actors from images taken randomly from movies. The use of images taken from Arab movies includes challenges such as non-uniform lighting, different and multiple poses for the actors and multiple elements with the actor or a group of actors. Additionally, the use of make-up, wigs, beards, and wearing different accessories and costumes made it difficult for the system to identify the personality of the same actor. The Arab Actors Dataset-AAD comprises 574 images sourced from various movies, encompassing both black and white as well as color compositions. The images depict complete scenes or fragments thereof. Multiple models were employed for feature extraction, and diverse machine learning algorithms were utilized during the classification and prediction stages to determine the most effective algorithm for handling such image types. The study demonstrated the effectiveness of the Logistic Regression model exhibited the best performance compared to other models in the training phase, as evidenced by its AUC, precision, CA and F1score values of 99%, 86%, 85.5% and 84.2% respectively. The findings of this study can be used to improve the precision and reliability of facial recognition technology for various uses as with movies search services, movie suggestion algorithms, and genre classification of movies.

Keywords: Artificial Intelligence, Machine Learning Algorithms, Face Recognition, Age Prediction, Naive Bayes (NB), Decision Tree (DT), Support Vector Machine (SVM), and Artificial Neural Network (ANN).

Introduction

Facial recognition has evolved into a vital research domain in automated computer vision because of its many implementations in protection, surveillance, entertainment sector, and sales strategy. Face recognition is the technique of recognizing persons grounded on their facial characteristics, this study is especially difficult because of the intrinsic variance in facial features resulting from aspects like pose, lighting, facial gesture, aging effects and also cosmetics and wigs usage. The integration of machine learning technique to identify the same actor in various forms (dueto makeup, wigs tailored to the character) can give in-depth perspective on analyzing human behavior and demographics.
Within the cinema sector and film industry, choosing appropriate actor for defined character is important to the box office success. Facial characteristics are the key factor in the actor casting decision, since it can impact the authenticity and trustworthiness of a character. On the other hand, detecting an actor from images taken from movies can be challenging because of using make-up to modify facial features

to be appropriate to a particular character. The goal of this research is to explore the implementation of machine learning algorithms in detecting actors and estimating their ages using a variety of Arabic movie scenes.

Lately, multiple research efforts have been carried out to maximize the accuracy of face recognition using machine learning algorithms. These algorithms are able to autonomously learning from data and generate predictions from the the learned patterns[1]. Naive Bayes (NB), Support Vector Machine (SVM), Decision Tree (DT), and Artificial Neural Network (ANN) are some of the popular machine learning algorithms[2,3] used for face recognition and age prediction. Earlier studies, however, primarily focused on face-centric datasets with consisting lightening, uniform resolutions, and minimal postures variations. As a result of the lack of such tightly controlled settings in real- life contexts, this approach has led to significant restrictions in the use of face recognition and age estimate techniques. Conversely, our work introduces an innovative method for overcoming the challenges in detecting actors and estimating their ages from images in Arabic movies. Numerous challenges that are frequently missing from well-chosen datasets are brought via these photos, such as:

1. Diverse Poses: Actors use different poses during film sequences, including sharp profiles to frontal views. Variations in poses may dramatically alter facial characteristics and add complexity in the identification process for standard face recognition systems.
2. Inconsistent Lighting: Films often have various lighting techniques, transitioning from brightly illuminated outdoor spaces to softly illuminated indoor spaces. The facial characteristics can be influenced by the changes in lighting, thereby complicating the task of algorithms in extracting reliable and dependable information for recognition.
3. Occlusions and Distracting Elements: In addition to the actor's face, movie scenes often include background items, clothing, props, and other actors. These elements might obscure facial attributes and introduce extra noise, potentially impairing the accuracy of face recognition systems.
4. Makeup and Facial Modifications: Makeup is frequently used by filmmakers to enhance or change an actor's appearance for a specific role. Algorithms find it difficult to rely particularly on facial cues for identification because these changes can drastically modify facial features.
5. Age Variations: Actors often take on roles for characters of different ages, resulting in aging-related modifications in facial features. Algorithms lacking specific training in age-related facial alternations may find these changes challenging.

The central contribution of our work lies in the development of the Arab Actors Dataset (AAD), an exclusive compilation of 574 images collected from different Arabic movies. Differing from earlier datasets, the AAD captures scenes that feature actors in full, encompassing their facial features, body poses, and the context of the movie. This comprehensive dataset provides the opportunity to explore the subtleties and challenges in actor recognition and age estimate in a tough and realistic environment. This dataset is a useful tool for examining the complexities and difficulties involved with age estimates and actor identification in a realistic and demanding film setting.

Our research addresses the limitations of previous studies by employing state-of-the-art machine learning algorithms and comparing them within the context of Arabic movies. Different challenges are faced in this context, like handling various lighting conditions, handling different poses, and incorporating props like costumes, wigs, and beards that have the potential to alter an actor's image. Actors’ age variations are also taken into consideration, evidenced by Nour al-Sharif who has depicted characters ranging from twenty to forty years old.

The significance of our research extends beyond the realm of face recognition. Our results have ramifications for a wide range of applications, from more sophisticated movie genre classification to improved movie search engines and recommendation systems. Our study elucidates the applicability and efficacy of face recognition technology, providing a paradigm shift in the context of Arabic cinema and utilizing the vast potential of the AAD dataset by improving the accuracy and reliability of facial recognition systems in culturally complex and challenging settings.

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https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

Related Works

The secure activities of an organization depend heavily on the capability to identify human faces. The field of machine learning has seen a surge of research focused on pattern recognition, with a specific emphasis on human face recognition. In this section exploration of recent developments in this area and examine various algorithm used for this task, along with their respective performances.

Rahul et al[4]. investigated through their review the fundamentals of face recognition through the use of Support Vector Machine (SVM) learning algorithms.

Xinyi et al[5]. conducted a survey that covered different aspects of face recognition technology. The survey started with an overview of face recognition in the Introduction Section. The history of face recognition was discussed in Section 2, while Section 3 focused on explaining the deep learning framework's pipeline. Section 4 provided an in-depth explanation of various face recognition algorithms, such as loss functions, embedding techniques, face recognition with massive IDs, cross-domain, pipeline acceleration, closed-set training, mask face recognition and privacy-preserving. In Section 5, a series of experiments were conducted to evaluate the effect of backbone size and data distribution. The frequently used training and test datasets were presented, along with comparison results, in Section 6. Applications of face recognition were discussed in Section 7, while Section 8 introduced competitions and open-source programs.

Tiago et al[6]. conducted a study in which they expanded upon their prior research conducted in 2014 and published in 2016. The original study explored how different face characteristics affected facial recognition systems. In their latest research, the authors evaluated the effectiveness of modern facial recognition systems against earlier models, concluding that deep learning algorithms can recognize faces under harsh conditions such as strong occlusion types of illumination, and strong expressions. Nevertheless, recognizing faces in images with low-resolution, extensive pose variations, and open-set recognition still pose challenges. To ensure the reproducibility of their findings, the authors utilized open-source and reproducible software, conducting experiments on six diverse datasets with five different face recognition algorithms. Furthermore, they offered access to their source code to allow others to reproduce the experiments.

In their study, Kai et al[7]. demonstrated the application of deep learning in recognizing human faces using both infrared and visible light images. According to the authors, the model outperformed other state of-the-art approaches, even when faced with variations in illumination.

In their paper, Fatimah et al[8]. proposed a novel approach by integrating the coherence of Discrete Wavelet Transform (DWT) with four distinct algorithms namely: Convolutional Neural Network (CNN), Eigen vector of PCA, error vector of principle component analysis (PCA), and Eigen vector of Linear Discriminant Analysis (LDA). The detection probability entropy and Fuzzy system were utilized to combine the four results. The accuracy of recognition was found to be dependent on the diversity and quality of the image database. The proposed combined method achieved recognition rates of 89.56% and 93.34% for the worst and best cases, respectively, which outperformed previous works where individual methods were implemented on specific image datasets.

The authors of the study, Omkar et al[9]. had the objective of implementing face recognition through the use of a single photograph or a series of faces recorded in a video. They employed a hybrid approach that leveraged both automated and manual methods to construct a large dataset containing 2.6 million images belonging to over 2.6 thousand individuals.

Using SVM techniques, Laith et al[10]. developed facial recognition systems. Image preparation was the first step. They used the Contrast stretching and Normalization size of the picture procedures. The image was then reduced to half its original size, the noise was removed, the processing time was cut in half, and features were extracted for classification.

A novel CNN architecture was presented by S. Meenakshi et al[11]. to eliminate the impact of changes in position and lighting, any occlusions, facial emotions, etc. Convolutional layers C1, C2, and C3 are used in the created approach to experiment with different feature maps in an effort to identify the most effective architecture. Moreover, this architecture contains a fully connected layer, a subsampling layer, and an input layer with a 32 x 32 pixel picture. After shrinking the image to 32 by 32 pixels, numerous tests are run on the ORL database to gauge the model's effectiveness. The 15-90-150 design has the highest accuracy of all the architectures, at 98.75%.

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P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

Putta et al[12]. employed PCA for feature reduction and extracted rotation and scale invariant characteristics from the normalized facial picture using the Gabor Wavelet. The classification was carried out by these three writers using SVM. The accuracy rates obtained on the three data sets: ORL, AR, and Grimace, respectively: 97.65%, 92.31%, and 100.00%.

The PCA approach was utilized by Ni et al[13]. to extract distinguishing characteristics. They also used gray scale conversion, region of interest (ROI), and Haar Cascade Segmentation for picture preprocessing. After that, the KNN algorithm is used to classify the data. While PCA+KNN approach accomplished an 81% recognition rate on a dataset research comprising 790 faces from 158 persons collected from various perspectives, 2D-PCA+KNN method achieved an accuracy rate of 96.88% on ORL database.

Zhiming et al[14]. proposed a facial recognition model. This model is based on the quantity of convolutional layer feature maps and the quantity of hidden layer neurons. As a result, facial recognition's accuracy has increased. The input layer, convolution layer 1, pooling layer 1, convolution layer 2, pooling layer 2, fully connected layer, and Softmax regression classification layer are all parts of the CNN architecture. As a result, they established the structure C1-C2-H, where C1 denotes the quantity of feature mappings in the first convolutional layer, C2 the quantity in the second convolutional layer, and H the quantity of hidden layer neurons. The ideal model, 36-76-1024, was discovered by Zhiming et al[13]. through numerous experimental experiments. Also, they achieved a facial recognition rate of 100% on the ORL database.

Throughout 2021, a team of researchers called Muhammad et al[15], via their experimental work, undertook a comparative analysis of four classical algorithms for machine learning using the ORL database. The comparison includes PCA, 1-Nearest Neighbor (1-NN), LDA, and SVM as the four machine learning methods. Then, the researchers developed the models, trained the classifiers, and retrieved features from the datasets. Finally, they used the 5-fold cross validation (n=5) method to assess how well these models performed. The accuracy ratings for the systems based on LDA, 1-NN, PCA, and SVM were 96%, 96.25%, 96.75%, and 98%, respectively. These outcomes show how well the SVM approach for face recognition works.

One of the CNN designs dubbed Residual Networks-50 was utilized by Yohanssen et al[16]. in their research to produce a system for recognizing faces. For the ImageNet test set, these cnn models achieve an error rate of 3.57%. The contribution of this research study is to establish efficacy ResNet architecture utilizing various configurations of hyper parameters such as the amount of hidden layers, the amount of units included in the hidden layer, number of iterations, and learning rate. Dataset size of 1050 photos split into the training and testing sets, with a ratio of 80% for the train dataset and 20% for the test dataset, to evaluate the model. They discovered that a learning of 0.0001, an epoch size of 100, and a step size of 150 result in a model with a 99% accuracy rate.

A comparison of machine learning techniques in the field of facial recognition was conducted by Benradi et a[17]l. These researchers acquired photographs from two databases: the ORL and the Sheffield face databases, which have 564 images of 20 people with identical dimensions of 220 220 pixels and 256-bit grayscale. They applied feature extraction utilizing the Scale-Invariant Feature Transform (SIFT), the Speeded Up Robust Features (SURF), the Features from Accelerated Segment Test (FAST), and LBP to these databases' two datasets, which were partitioned into train and test datasets. SVM, KNN, PCA and 2D-PCA algorithms are used in classification to develop prediction models using the feature vectors collected from the face photos. The forecasting models were examined, the outcomes demonstrated that the suggested approaches, including SIFT+SVM, LDA+KNN, PCA and 2D-PCA performed with the following accuracy rates in the ORL Dataset: 99.16%, 96%, 92.50% and 96.25%. The accuracy ratings for the algorithms SIFT+SVM, LDA+KNN, PCA and 2D-PCA on the Shiefilled Dataset are 99.44%, 96%, 27.11% and 43.10% respectively. Definitely SVM out performs the other investigated algorithms, according to Benradi et al[17].

The two algorithms will be combined in 2022 in order to develop a facial recognition system, according to Zahraa et al[18]. The SVM method is the first one. The second is a brand-new meta heuristic technique named Rain optimization algorithm (ROA), which was motivated by rainfall. If its parameters are properly adjusted, this approach can find both local and global extremism. The aim of the Radial Basis Function (RBF) kernel SVM's C and parameters optimization in this work is to use ROA. They therefore were using the Yale face dataset to assess the proposed approach. By carrying out an n-fold validation (n = 10) the authors were able to achieve an 86% identification rate.

The study conducted by Zohaa et al[19] focuses on the identification of adverse drug reactions (ADRs). To increase accuracy, they suggest fusing Artificial Neural Network (ANN) classifiers with Latent Semantic Analysis (LSA). The study shows the efficacy of the LSA-ANN technique in ADR extraction by including frequent user evaluations and comments during data gathering. The F-measure of 85% is superior than the baseline of 82%, according to the results. For improved ADR identification, the authors propose further research on real-time reviews and deep learning-based advanced word embedding.

A paper by Safa et al[20]. explores the application of machine learning algorithms in healthcare, particularly for anemia disease classification. It underscores the significance of processing large healthcare datasets using digital analytics and classification tools. The study conducts a comparative analysis of twelve classification algorithms, revealing that Logitboost, Random Forest, XGBoost, and Multilayer Perceptron performed well, with XGBoost achieving the highest accuracy. Subsequently, XGBoost is employed for classifying new datasets in Hematology studies in Iraq.

Connecting this with machine learning algorithms used for face recognition, the paper highlights the broader utility of machine learning techniques in healthcare and beyond. Just as these algorithms effectively classify medical conditions, they can also be harnessed for tasks like face recognition, offering promising results. However, it's crucial to ensure high-quality and diverse training data for both healthcare and face recognition applications, as well as acknowledging potential errors, especially in complex scenarios. Overall, this paper underscores the significant potential of machine learning algorithms in enhancing medical diagnoses and treatments and suggests their relevance in various domains, including face recognition.

Our work has filled in many gaps in the field of face recognition and brought in new insights that have greatly improved the discipline. A significant gap in the existing data has been addressed through the introduction of a new collection of Arabic actors.

A novel approach has been developed to potentially revolutionize the field of film analysis: discerning the year of a picture's creation by leveraging actor ages.

A comprehensive exploration of machine learning algorithms within the Arabic film industry yielded valuable insights into the challenges posed by uneven lighting, diverse poses, and alterations induced by cosmetics and props on facial features. Consideration of performer ages further enhanced understanding of the complexities associated with facial recognition.

Our study is in line with the most recent developments in the area and makes original contributions that close current gaps and provide useful applications. It adds a great deal to the body of work already done and emphasizes how machine learning is revolutionizing facial recognition and how it may be used in a variety of fields.

Addressing limitations present in prior research and techniques, such as the utilization of uniform resolution photos exclusively featuring faces, the Arabic Actors Dataset (AAD) was developed using 574 photos extracted from 14 Arabic films. This dataset aims to mitigate challenges arising from factors like uneven lighting, diverse stances, and the presence of cosmetics and accessories.

Our dataset is unique in that it contains scenarios with several features, a range of actor appearances, and varying age stages for the same actor. Our dataset closes a sizable gap in the literature for Arabic actors. Our dataset adds complications seen in real-world circumstances, whereas earlier research concentrated on controlled settings. Also here are some particular instances of how or study might overcome the limitations of earlier research and techniques:

1- Our study can address the lack of variety in current datasets by creating a new dataset of Arabic actors. This will make it possible for researchers to create facial recognition models that are more reliable and cross-population suitability.
2- Our study can solve the problem of face identification in low-resolution photos by creating a novel technique for determining the year of a movie's creation based on the ages of the performers. This is due to the fact that, even in low-resolution photos when other face traits are hard to make out, performers' ages are frequently discernible.
3- Through a detailed evaluation of machine learning algorithms in the Arabic film business, our study can assist in identifying the particular difficulties caused by a range of lighting conditions,

2024, 21(12 Suppl.): 4146-4162
https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

different stances, and facial changes caused by products and makeup. For these particular circumstances, more reliable face recognition models may be created using the information provided.

Materials

This section addresses the main research questions that our work has tackled:

1- Dataset creation: What problems with facial recognition occur when you use pictures from Arabic motion pictures that have different lighting, different stances, and other scene elements?
2- Models for Image Embedding: In terms of facial recognition for Arabic actors, how well do several image embedding models—like Inception v3, OpenFace, SqueezeNet, VGG-16, VGG-19, Painters, and DeepLoc—compare?
3- Machine Learning Algorithms: When training a classifier for actor classification based on face data, how do several machine learning algorithms—SVM, NB, Constant, SGD, KNN, DT, AdaBoost, CN2 Rule Induction, Gradient Boosting, Logistic Regression, RF, and ANN—compare?
4- Age prediction and Actor Categorization: In terms of prediction algorithms, how trustworthy are SGD and logistic regression for photos from different Arabic films?
5- Performance Assessment: Which measures are appropriate for assessing the effectiveness of the predictor and classifier in facial recognition systems, such as precision, AUC, F1 score, specificity, and LogLoss?
6- Practical Applications: What contributions may the results of this study make to genre analysis, recommendation engines, and movie search engines? Also; how can improving facial recognition system accuracy and reliability help us understand how the film business is developing and how it may bring us insights on human behavior and demography?

Through this research answer to the above questions will be clarified.

Arabic Actor Dataset-AAD Collection and Analysis

Face picture databases are required for the deployment and evaluation of a facial recognition system. Table 1 shows some of the options that have a lot of interest among researchers where whole image collection was captured under various facial expression conditions.

Table 1. Some Face picture databases.

Database Name	No. of Pictures	No. of Persons	Image Resolution	Lightening
GRIMACE[12]	360	18	200×180 pixels	identical lighting conditions
ORL[12, 21]	400	40	112 × 92 pixels	includes subtle differences in illumination, in pose, and face characteristics
YALE[22]	165	15	----	different illumination

As can be seen from Table 1 images were identical in resolution for each system; and only a face occur in each image as can be seen in Fig. 1.

2024, 21(12 Suppl.): 4146-4162
https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986

(a) ORL Dataset

(b) YALE Dataset

Figure 1. Sample images. (a) ORL dataset. (b) YALE Dataset.

In this research a new dataset was built by collecting 574 images from 14 different Arabic movies for 14 actors (7 women and 7 men) as shown in Table 2 and Table 3. These images were divided into two separate sets, the training and testing sets. The model will be trained using the first one, and evaluated using the second. Training set consisted of 468 images; while testing set had 106 images.

Table 2. System Database (14 movies, 14 actors, 574 images)

No.	Movie Title	Production Year
1	From Home To School من البيت للمدرسة	1972
2	When Men Cry عندما يبكي الرجال	1984
3	Premeditation مع سبق الاصرار	1979
4	Bunch Of Crooks شلة المحتالين	1973
5	Swindlers النصابين	1984
6	Me انا	1985
7	Women In City نساء في المدينة	1977
8	Streets Of Fire شوارع من نار	1984
9	Let Me Revenge دعوني انتقم	1979
10	Sunset And Sunrise غروب و شروق	1970
11	Dancer And Drummer الراقصة والطبال	1984
12	Satan's Daughters بنات ابليس	1984
13	Revenge Game لعبة الانتقام	1992
14	The Struggle of the Grandchildren صراع الاحفاد	1989

Table 3. Actors with their ages

No.	Actor Name	Birth Date	Death Date
1	Nabila Aubaid نبيلة عبيد	1945	---
2	Mahmood Yasin محمود ياسين	1941	2015
3	Nour al-Sharif نور الشريف	1946	2015
4	Mahmood Al-Mileegy محمود المليجي	1910	1983
5	Layla Alui ليلى علوي	1962	---
6	Madiha Kamel مديحة كامل	1948	1997
7	Sayed Zayan سيد زيان	1943	2016
8	Husain Fahmi حسين فهمي	1940	---
9	Mirvat Ameen ميرفت امين	1948	---
10	Fareed Shawqi فريد شوقي	1920	1998
11	Shwikar شويكار	1936	2020
12	Suad Husni سعاد حسني	1943	2001
13	Isaad Younis اسعاد يونس	1950	---
14	Twfiq Al-Thiqin توفيق الذقن	1923	1988

The use of images taken from Arab movies includes dealing with several challenges, such as non-uniform lighting in the images, Different and multiple poses for the actors, One image contains several elements (such as the furniture in the room) with the actor or a group of actors, and not as previous researches for face classification and recognition used to deal with images that include the face of the person only, the use of make-up, wigs, beards, and wearing different accessories and costumes commensurate with the type of role played by the actor (for example, the actress Madiha Kamel in some pictures wearing the Egyptian Abaya, the Egyptian veil, and the Egyptian Niqap) made it difficult for the system to identify the personality of the same actor, and different age stages were chosen for the same actor (for example, Nour al-Sharif. A picture was taken from a movie; he was twenty years old, with other pictures of the same actor from another movie, and he is forty years old).

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https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

Also, the images taken from various movies, including black and white, and color ones (old and new movies). Additionally, there are images depicting complete scenes, while others capture only partial scenes. Moreover, as far as current knowledge indicates, there exists no dedicated dataset for images sourced from Arab films. The Arabic Actors Dataset (AAD) was conceived and developed, employing an 82/18 split ratio for the training and testing sets. Sample images from AAD are illustrated in Fig. 2.

Figure 2. Sample images from AAD.

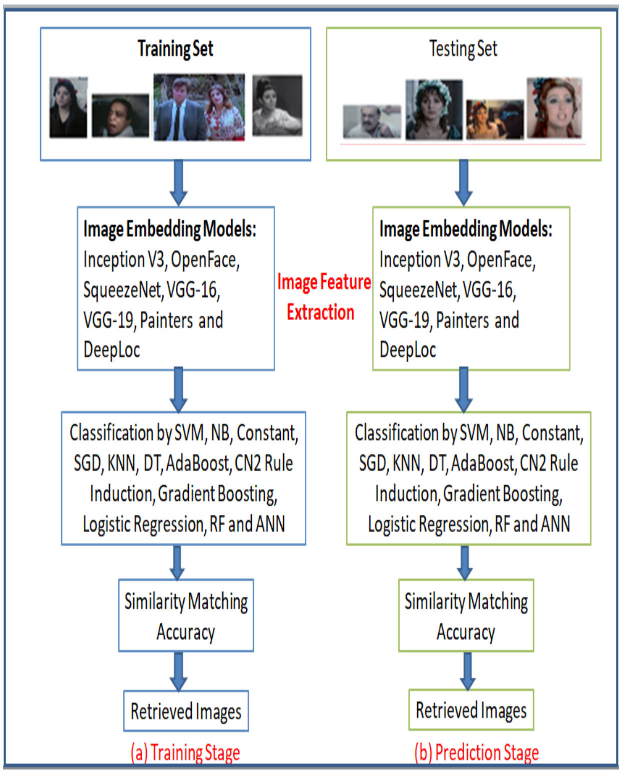

Figure 3. System Components and Workflows.

Method

Complete system components and workflow is shown in Fig. 3 below. ADD was prepared and divided for training and testing. Image feature extraction was done for both training and testing sets. Then machine learning algorithms were used for the classifier and predictor. Performance evaluation was made to select the most accurate algorithm to be used to predict the movie production year for new images with known attributes. Fig. 4 below is an algorithmic representation of the methodology.

Feature Extraction

From the foregoing, images with similar specifications that were mentioned; represent a great challenge for image embedding models which is performed to obtain a low-dimensional representation of a given image that accurately captures its key elements and allows for straightforward comparison with other embedding's[23, 24].

There are several face recognition models available for free that can be used for various applications such as OpenCV[25,26] Face Recognition, OpenFace[27], FaceNet[28], DeepFace[29] and DLib[26] Face Recognition. The best model for your application will depend on your specific requirements and constraints.

In this research several image embedding models were used such as Inception v3, OpenFace, SqueezeNet, VGG-16, VGG-19, Painters and DeepLoc. A general summary on each model is shown in Table 4 below. The N/A means that there is no top-1 or top-5 accuracy information available for the model.

1. Arabic Actor Dataset (AAD) Creation:
   - Collect 574 images from 14 different Arabic movies featuring 14 actors.
   - Divide the dataset into training (468 images) and testing sets (106 images).
2. Image Feature Extraction:
   - Initialize a list to store the extracted features.
   - For each image in the AAD:
     - Apply image embedding models to obtain low-dimensional representations.
     - Add the extracted features to the list.
3. Classifier Training:
   - Initialize the training set features and labels.
   - For each image in the training set:
     - Assign the corresponding image features from the extracted features list.
     - Assign the label based on the actor's identity.
   - Train machine learning algorithms using the training set features and labels.
4. Face Recognition
   - Initialize the testing set features and predicted labels.
   - For each image in the testing set:
     - Assign the corresponding image features from the extracted features list.
     - Use trained machine learning algorithms to predict the actor's identity.
     - Store the predicted label.
5. Movie Production Year Calculation:
   - For each image in the testing set.
     - If predicted label matches the actual label:
       - Use the predicted movie Production Year from the algorithm as the output.
     - If the predicted label does not match the actual label:
       - Compute movie production year using actor's birth year and their age at the time of image.
6. Performance Evaluation:
   - Calculate evaluation metrics for the trained classifier and prediction models
   - Compare the performance of different machine learning algorithms.
   - Identify the most accurate algorithms for actor identification and movie production year prediction.

Figure 4. Algorithmic Representation of the Methodology.

Table 4. A Comparison of Image Embedding Models.

Model	Description	Number of parameter	Top-1 accuracy %	Top-5 accuracy %	Image Type
Inception v3[30]	A deep neural network designed for image recognition, with improved efficiency over previous Inception models.	23.8 million	78.8%	94.4	General Image Classification
OpenFace[31]	A face recognition model that uses deep neural networks to extract features from faces, designed to work under different conditions	2.3 million	92.2%	94.	Face Recognition

SqueezeNet[32]	A lightweight neural network designed for image classification with low memory and computational requirements	0.72 million	57.5%	80.3	General Image Classification
VGG-16[33,34,35]	A deep neural network with 16 layers, designed for image recognition with a focus on improving accuracy	138.3 million	71.5	90.2	General Image Classification
VGG-19[36]	A deeper version of VGG-16 with 19 layers, designed to improve accuracy further	143.7 million	72.3	90.8	General Image Classification
Painters[37]	A neural network designed for image classification that can distinguish between paintings by different artists	16.6 million	80.2	N/A	Painting Classification
DeepLoc[38]	A neural network designed for protein localization prediction in microscopy images	1.1 million	85.7	N/A	Protein Subcellular Localization

Classifier Training

Machine learning algorithms like (SVM, NB, Constant, SGD, KNN, DT, AdaBoost, CN2 Rule Induction, Gradient Boosting, Logistic Regression, RF and ANN) were used to build a model that can classify and recognize actor's faces. Table 5 shows a general comparison among these algorithms. Where in Constant algorithm predict the most frequent class or mean value from training set; this is related to baseline models in machine learning[33].

Table 5. Machine Learning Algorithms Compared for Face Classification and Recognition.

Algorithms	Advantages	Disadvantages	Suitable Application
SVM[39,40]	Works well on high-dimensional data	Can be sensitive to the choice of kernel function	Face recognition, classification
NB[41,42,43]	Simple and easy to implement	Assumes independence of features, which may not hold in practice	Face classification
Constant[44]	Simple and interpretable	May not perform well on complex data	Face classification
SGD[45]	Efficient for large-scale datasets	May not converge to a global minimum	Face classification
KNN[13]	Simple to implement and interpret. Good for small datasets, works well with local patterns.	Can be computationally expensive for large datasets. May not work well with high-dimensional data.	Face classification
DT[46]	Easy to understand and interpret. Can be effective in classification tasks with clear decision boundaries.	Prone to over fitting, especially with complex datasets. May not work well with continuous data.	Classification or Recognition
AdaBoost[47]	Can achieve high accuracy with multiple weak classifiers. Good for face recognition tasks.	Prone to over fitting if weak classifiers are too complex. Can be computationally expensive.	Recognition
CN2 Rule Induction[48]	Can handle complex datasets and produce interpretable rules. Can be effective in face classification tasks.	May not work well with small datasets. Can be sensitive to noise and outliers.	Classification

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https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
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Gradient Boosting[49]	Can achieve high accuracy with multiple weak learners. Good for face recognition tasks.	Can be computationally expensive for large datasets. Prone to over fitting if weak learners are too complex.	Recognition
Logistic Regression[50,51]	Simple to implement and interpret. Can be effective in face classification tasks when using binary outcomes.	May not work well with nonlinear relationships between features and outcomes.	Classification
RF[52]	Can achieve high accuracy with multiple decision trees. Good for face recognition tasks.	Can be computationally expensive for large datasets. May not work well with imbalanced data.	Recognition
ANN[22]	Highly effective in face recognition tasks when trained with large datasets.	Can be expensive to compute and needs a lot of training data. And is prone to fitting too tightly.	Recognition

Face Recognition

This is done by using test set. In this stage; the output of image embedding is the input to prediction model. Prediction is done using learning algorithms like (SVM, NB, Constant, SGD, KNN, DT, AdaBoost, CN2 Rule Induction, Gradient Boosting, Logistic Regression, RF and ANN) to select the most accurate result among them. Confusion matrix was used to summarize the predictions made by a model on a set of test data, comparing them to the actual values or labels of the data. The matrix is constructed as follows: (1) the rows of the matrix correspond to the actual or true labels of the data. (2) The columns of the matrix correspond to the predicted labels of the data. (3) Each cell in the matrix represents the number of times a data point was classified or predicted as belonging to a certain class, given its true label.

Calculate Movie Production Year

If the image is classified correctly by the machine learning algorithm, use the predicted movie production year from the algorithm as the output. Else if the image is misclassified, compute the movie production year using Eq. 1:

Movie Production Year = Actor Birth Year + Age of Actor ….1

Where the Actor Birth Year is assumed to be known.

Results and Discussion

Table 6 contains a comparison of the results obtained from using image embedding models for image feature extraction.

Table 6. A Comparision of Results from Image Embedding Models.

Model Name	Training (Images successfully embedded)	Training (Skipped Images)	Testing (Images successfully embedded)	Testing (Skipped Images)
Inception v3	468	0	106	0
SqueezeNet	468	0	106	0
VGG-16	468	0	106	0
VGG-19	Run time error	468	Run time error	106
Painters	468	0	106	
DeepLoc	468	0	106	0
OpenFace	349	119	89	17

Despite the fact that OpenFace was specifically designed for face recognition but it had the worst result in image embedding for ADD. VGG-19 had a run time error. While other models (Inception v3, SqueezeNet, Painters, and DeepLoc and VGG-16) had identical results thus Inception v3 was used to train the classifier and predictor.

Tables 7 shows a comparison of results obtained from using these machine learning algorithms in training the classifier when using Inception v3 embedding model. The table shows Training Time,

2024, 21(12 Suppl.): 4146-4162
https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

Test Time, AUC-ROC, Accuracy, F1, Precision, Recall, LogLoss, and Specificity.

Table 7. Results from Training Classifier.

Model	Train time(s)	Test time(s)	AUC	CA	F1	Precision	Recall	Logloss	Specificity
Logestic Regression	69.901	5.652	0.990	0.855	0.842	0.860	0.855	0.431	0.973
Neural Network	50.885	10.841	0.988	0.846	0.835	0.830	0.846	0.551	0.976
SGD	27.283	11.391	0.906	0.838	0.821	0.812	0.838	5.609	0.983
SVM	41.302	13.183	0.985	0.797	0.765	0.786	0.797	0.698	0.944
KNN	9.001	9.986	0.958	0.767	0.733	0.727	0.767	1.824	0.960
Gradient Boosting	2364.893	6.130	0.913	0.684	0.675	0.671	0.684	2.227	0.949
Random Forest	10.972	4.851	0.903	0.652	0.619	0.609	0.652	2.882	0.929
Tree	100.377	0.128	0.742	0.534	0.529	0.539	0.534	14.725	0.931
AdaBoost	13.689	6.130	0.718	0.515	0.516	0.518	0.515	16.753	0.933
CN2 rule inducer	33367.200	5.685	0.755	0.476	0.475	0.477	0.476	1.997	0.927
Constant	0.015	0.051	0.491	0.267	0.113	0.071	0.267	2.256	0.733
Naïve Bayes	21.653	8.757		0.060	0.065	0.238	0.060		0.989

As can be seen this research answered the previously specified questions in the methodology section as follows:

1. The solution to Dataset Creation: A new dataset, the Arabic Actors Dataset-AAD, was developed to solve these issues. It comprises 574 photos for 14 actors from 14 distinct Arabic films. The circumstances in the collection are varied and include uneven illumination, a range of positions, and distinct scene features.
2. Models for Image Embedding: OpenFace produced less than ideal results even though it was intended for facial recognition. Runtime faults were encountered by VGG-19. The outcomes of the remaining models, which included Inception v3, were the same, and Inception v3 was selected for further training.
3. Machine Learning Algorithms: Results: Logistic Regression performed better in training, showing high values for precision, recall, AUC-ROC, accuracy, and F1 score.
4. Actor classification and age prediction: Result: Testing shows that both SGD and logistic regression are reliable methods for classifying actors in photos from various Arabic films and estimating ages.
5. Performance Assessment: Based on the used metrics, the algorithms SGD and logistic regression are shown to be dependable as will be seen in the next section.
6. Applications in Practice: By increasing the accuracy of facial recognition, this research can help with genre analysis, recommendation engines, and movie search engines. Also this research can give us insights into how people behave and what's trending in movie business.

Performance Evaluation:

Evaluate the Performance includes; (a) Evaluate the classifier; after training system classifier, evaluations of different embedding models and machine learning algorithms were performed to see their performance

2024, 21(12 Suppl.): 4146-4162
https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986

on the training set using metrics like Area Under Curve (AUC), Precision, Classification Accuracy (CA), F1 score, specificity and LogLoss. If accuracy used as a measure for performance then the best algorithm used for classification is Logistic Regression 85.5 % followed by Neural Network algorithm with accuracy 84.6%. (b) Evaluate predictor; the confusion matrix allows us to calculate several metrics that are commonly used to evaluate the performance of a classification model, including accuracy, precision, recall, and F1 score. These metrics help us to understand how well the model is able to correctly identify different classes of data, and to diagnose any specific areas where the model may be performing poorly[52]. Fig. 5 shows confusion matrix for Logistic Regression; where blue cells used for correct result with its ratio and pink color used for wrong result with its ratio. This figure shows prediction results when using test set including 106 random selected images.

A comparison of the results obtained from using different machine learning algorithms shown in Table 8 is performed. Both Logistic Regression and SGD has the highest equal correct results thus they can be considered as the best machine learning algorithms used for prediction for images taken randomly from different movies.

The results obtained from Table 8; are used in the selection of the best performing algorithm to be used to predict the movie production year for new images with known attributes.

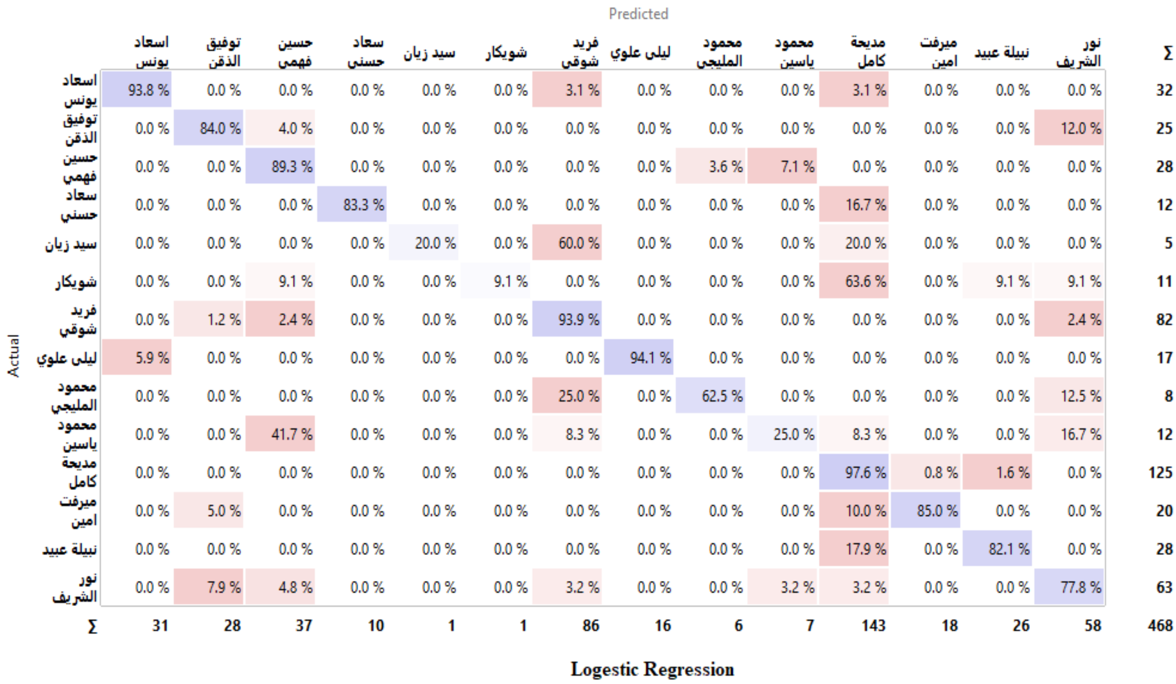

Figure 5. Confusion Matrix for Logistic Regression Learning Algorithm.

Table 8. Results of Different Machine Learning Algorithms in Prediction.

No.	Algorithm Name	Correct Prediction	Wrong Prediction
1	Logistic Regression	85	21
2	Neural Network	80	26
3	SGD	85	21
4	SVM	82	24
5	Random Forest	71	35
6	AdaBoost	53	53
7	Gradient Boosting	80	26
8	KNN	80	26
9	CN2 rule inducer	50	56
10	Tree	47	59
11	Constant	25	81
12	Naïve Bayes	11	95

2024, 21(12 Suppl.): 4146-4162
https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

Implications and Suggestions

Numerous implications arise for the subject of face recognition and its applications from our research. **Firstly**, address the lack of diversity in current face recognition datasets by introducing a new set of Arabic actors. More resilient and broadly applicable face recognition models with a greater range of applications may result from this. **Second**, our novel technique for determining the creation year of a film from the ages of its performers might completely change the field of cinema analysis. Using this technique, movies may be automatically dated and patterns in casting decisions can be found across time. **Third**, the particular difficulties presented by uneven lighting, a range of positions, and makeup and prop-induced facial alterations have been clarified by our extensive analysis of machine learning algorithms in the Arabic film business. With this data, more reliable face recognition models for these particular circumstances may be created.
The development of face recognition applications in the real world is also affected in a variety of ways by our study. Our research might be applied, for instance, to enhance the precision of facial recognition software used in surveillance and security applications. Furthermore, new face recognition applications in social media, marketing, and entertainment might benefit from our research.

Limitations and Future Work:

Future research should address the limitations of our study. **Initially**, the size of our Arabic actor dataset is quite limited. A bigger dataset would enable us to create more reliable models and more thoroughly assess the effectiveness of various facial recognition systems. **Second**, still working on our technique to determine the year a movie was made based on the ages of the performers. Additional investigation is required to enhance the precision of this approach and expand its use to a broader spectrum of films. **Third**, the Arabic film business was the main focus of our analysis of machine learning techniques. Testing these algorithms on additional datasets, such collections of faces from other racial and cultural backgrounds, would be fascinating.
Intend to investigate the use of convolutional neural networks on our dataset for actor recognition and classification. Also intend to improve our approach to inferring the year of a movie's creation based on the ages of the actors, broaden our dataset of Arabic actors, and assess our machine learning algorithms on more datasets in order to solve these constraints in future work.

Conclusion

Using images from Arabic movies, this paper concluded with a comparative review of several image embedding models and machine learning techniques for face identification. Different lighting situations, actor positions, and the presence of several items in the scenes were just a few of the difficulties that the images brought. Furthermore, the use of makeup, accessories, and costumes made it harder to distinguish between performers, especially when they were portraying different age groups. Despite these challenges, our analysis revealed valuable insights. Comparing a number of image embedding models, it was discovered that Inception v3 produced the best trustworthy findings for feature extraction. Then assessed several machine learning age prediction and actor categorization strategies. During the training phase, Logistic Regression performed better than other methods, displaying high AUC, precision, classification accuracy, and F1 score values. Both Logistic Regression and SGD showed to be reliable prediction algorithms throughout the testing phase.

This research has major effects for applications such as movie search engines, recommendation platforms, and genre evaluation. This research aids to understand changes in cinematic trends and provides valuable insight information on human actions and demography, especially concerning aging. This is achieved through improving precision and reliability of face recognition technology.
In spite of the constraints of this research, such as a limited dataset made up entirely of Arabic movies and the intrinsic difficulties in recognizing actors, our research acts as the foundation for future developments in face recognition systems. Future research should expand their datasets to incorporate larger and diverse populations to enhance the extent of their finding's applicability. Additionally, including other elements like facial expressions and utilizing deep learning methods might help to increase the accuracy of age prediction. These research directions show potential for improving facial recognition technologies and broadening their uses outside the purview of our current study.

2024, 21(12 Suppl.): 4146-4162
https://doi.org/10.21123/bsj.2024.8996
P-ISSN: 2078-8665 - E-ISSN: 2411-7986
Baghdad Science Journal

Authors' Declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not mine, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at University of Baghdad.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- No potentially identified images or data are present in the manuscript.

Authors' Contribution Statement

A.M.A. led research design, methodology, and CNN implementation for Arab movie scene classification. N.R.A. provided guidance, reviewed manuscripts, validated methodologies, and offered valuable insights. Both authors approved the final manuscript, recognizing their roles in completing the research successfully.

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التنبؤ بسنوات إنتاج الأفلام من خلال التعرف على وجوه الممثلين باستخدام التعلم الآلي

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الخلاصة

قارنت هذه الدراسة خوارزميات تعلم الآلة المختلفة لتحديد والتعرف على الممثلين واستخراج عمر الممثلين من الصور المأخوذة عشوائيًا من الأفلام العربية. ومن ثم احتساب سنة انتاج الفلم من اعمار ممثليه التي توصل اليها النظام. يتضمن استخدام الصور المأخوذة من الأفلام العربية تحديات مثل الإضاءة غير الموحدة ، وطرح مختلف ومتعدد للممثلين وعناصر متعددة مع الممثل أو مجموعة من الممثلين. بالإضافة إلى ذلك ، فإن استخدام الماكياج والشعر المستعار واللحية وارتداء الملحقات والأزياء المختلفة الخاصة بالشخصية التي يؤديها الممثل جعل من الصعب على النظام تحديد شخصية الممثل نفسه (الشخصية الحقيقية). تم اختيار مراحل عمرية مختلفة للممثل نفسه، مثل نور الشريف التي تبلغ من العمر عشرين عامًا في احد الافلام وأربعين عامًا في فلم اخر. وتم انشاء مجموعة بيانات الممثلين العرب هي مجموعة بيانات من 574 صورة مأخوذة من أفلام مختلفة، بما في ذلك افلام الأسود والأبيض والافلام الملونة. كما تمثل بعض الصور مشهدًا كاملاً بينما كان البعض الآخر جزءًا من مشهد. تمت المقارنة بين عدة نماذج لاستخراج الميزات. كما تم إجراء مقارنة بين مجموعة من خوارزميات التعلم الآلي المختلفة في مرحلتي التصنيف والتنبؤ لمعرفة الخوارزمية الأفضل في التعامل مع مثل هذا النوع من الصور. أظهرت الدراسة فعالية نموذج الانحدار اللوجستي الذي أظهر أفضل أداء مقارنة بالنماذج الأخرى في مرحلة التدريب، كما يتضح من قيم المنطقة تحت المنحنى (AUC) والضبط والدقة وF1 التي بلغت 99٪ و 86٪ و 85.5٪ و 84.2٪ على التوالي. يمكن استخدام نتائج هذا البحث لتعزيز الدقة والاعتمادية لأنظمة التعرف على الوجه لتطبيقات متنوعة مثل محركات البحث عن الأفلام وأنظمة التوصية بالأفلام وتحليل نوع الأفلام.

الكلمات المفتاحية: الذكاء الاصطناعي، وخوارزميات التعلم الآلي، والتعرف على الوجوه، والتنبؤ بالعمر، ناييف بايسين، شجرة القرار، آلة المتجهات الداعمة، والشبكة العصبية الاصطناعية.