Exploring Deep Learning Approaches for Effective Gender Identification in Face Images

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Abstract
Computer vision extensively investigates the field of automatic gender determination from face photographs. Although humans find this activity rather straightforward, it presents a significant obstacle for robots. This article is a study that proposes a strategy for classifying gender based on feature vectors obtained from facial recognition. The procedure starts by using face recognition and preprocessing techniques on incoming photos, transforming them into a standardized format. Subsequently, a face recognition model is used to extract feature vectors that accurately describe the facial traits inside the designated feature space. Ultimately, the feature vectors are categorized using machine learning methodologies.
This paper presents a sophisticated approach for classifying gender using VGG Face and Deep Belief Networks, which includes adding shifted filter responses. The study examines many models, such as CNN, VGG 16, ResNet50, Inception v3, and EfficientNet, and finds that ResNet152 has greater performance. The ResNet152 model has superior performance compared to other models, with an estimated 9% improvement. This is attributed to its enhanced ability to handle outliers, surpassing the capabilities of earlier models.

Keyword: Gender classification, convolutional neural systems , SVM , LFW, FERET, CNN, VGG 16, Resnet50, inception v3, and EfficientNet

Introduction

Precise gender classification has the potential to improve several fields such as computer vision systems, biometric identification systems, credit card verification systems, visual surveillance systems, and data collecting and security systems [1]. The field of study has had a significant impact on advancements in machine learning, image processing, and human-computer interaction [2]. There has been a surge of study in response to the growing demand from companies in the ability to categorize faces by gender in digital photographs and videos [3]. Gender recognition may be applied in several helpful circumstances, as outlined below.

Techniques for enhancing communication between computers and individuals: A more resilient foundation for human-computer interaction might be created by accurately discerning a person's characteristic, such as gender [4]. An example that demonstrates this concept is a robot engaging in a conversation with a human. To have a meaningful exchange, the robot would need knowledge on the individual's gender, such as whether they identify as Mr. or Ms.

Advanced surveillance systems have the potential to enable the restriction of access to certain regions of a train car or dormitory only to individuals of a certain gender [6].

Material-based indexing and searching: The increase in the number of electronic devices such as cameras has led to a proportional increase in the amount of photographic and cinematic material [7]. Automated structures based on computer vision would greatly simplify the process of indexing and annotating information such as the count of individuals in an image or video, as well as their age and gender [8].

Biometrics: The identification of an individual's gender aids in expediting the search for their facial data in a database, hence enhancing the efficiency of biometric techniques like as facial recognition [9]. Additionally, it may be used to improve face recognition by using distinct face recognizers for each gender in order to get the highest possible recognition rates. This is an extra benefit [10].

Personalized advertisements: the use of digital billboard technologies on flat-panel displays enables accurate and specific targeting of customers. Targeted advertising enables billboards to provide adverts that are very relevant to the individual seeing them [11]. Gender is an exemplification of a quality that aligns with this depiction [12]. Upon detecting a male individual, the billboard has the potential to display advertisements for wallets. Conversely, if a female is recognized, it is possible for the billboard to exhibit advertisements for purses [13]. In India, there has been an increase in sales at vending machines that provide drinks according on the customer's gender [14].

Literature Work

Utilize our data to experiment with a Convolutional Neural Network (CNN) model. CNN has a success rate of 88.3%, establishing its superiority over other machine learning approaches [15]. Enhance classifier performance by using successive iterative detection. We will provide first findings from a dataset collected in Turkey [16]. Enhances the current highest level of performance by accurately detecting 97.4% of faces belonging to Asian celebrities [17]. Artificial Neural Network (ANN) outperforms Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) in terms of performance. This study used a total of 2,734 primary data points. Subsequent research will analyze the role of gender categorization in Bahasa Indonesia speech recognition [18]. Furthermore, an analysis was conducted on the 20 characteristics that were used to create prediction models. Our work may be helpful to future academics [19]. Regularization minimizes the disparity in accuracy between the training and test sets, without exceeding this reduction. Data augmentation has the potential to decrease overfitting [20]. The OU-ISIR and CASIA datasets are compared based on gender and performance assessment criteria, including recall, precision, and accuracy [21]. The face model was trained using both a publicly accessible dataset from Kaggle and a dataset specifically created for this purpose. This configuration enhances the precision of the test [22]. Generated a novel Tim and Abi persona to analyze four software engineering job listings. Both individuals experienced sexism. The online recognizer transcribes audio recordings in the wav format into written text. Diarization in an audio recording accurately identifies the speakers and their respective speaking intervals. The model has a voice recognition accuracy of 92%. The findings of this work may be used to transcription platforms and other speech devices [24]. Demonstrate the superior performance of GAHL compared to commonly used machine learning models such as logistic regression, decision trees, and SVMs with polynomial and radial basis function kernels [25]. The results of our study will benefit healthcare professionals and patients by eliminating the need for repetitive model testing in maternity wards [26]. By combining Artificial Neural Networks (ANN) with Whale Optimization Algorithm (WOA), we achieved better results compared to Bayesian networks, regression, decision trees, support vector machines, and ANN alone. Our approach achieved an accuracy of 98%, precision of 97.16%, and recall of 99.67% [27]. The research found that high-energy vocal pieces include unique and identifiable material. Gender influences the ability to differentiate shouted speech [28]. This method might potentially aid the United Nations (UN), World Health Organization (WHO), and government agencies in implementing prompt-response initiatives to enhance women's rights, humanitarian efforts, and security [29].

Proposed Approach

3.1 Deep Belief Networks: DBN stands for Deep Belief Networks COSFIRE Grouping of Shifted Filter Responses (COSFIRE) is a trainable filter method which verified to be current in numerous computer vision tasks. Feature reduction

A belief net is a stochastic variable-filled directed acyclic graph that is used in mathematics to represent a random variable distribution. There are a few variables that can be observed, and we wish to address two of them: There is an inference problem for the variables that have not been observed: The learning problem is the process of adjusting the interactions between variables in order to increase the likelihood that the network will generate observable data.

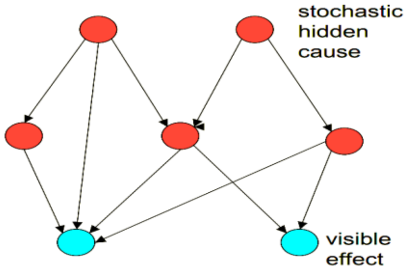
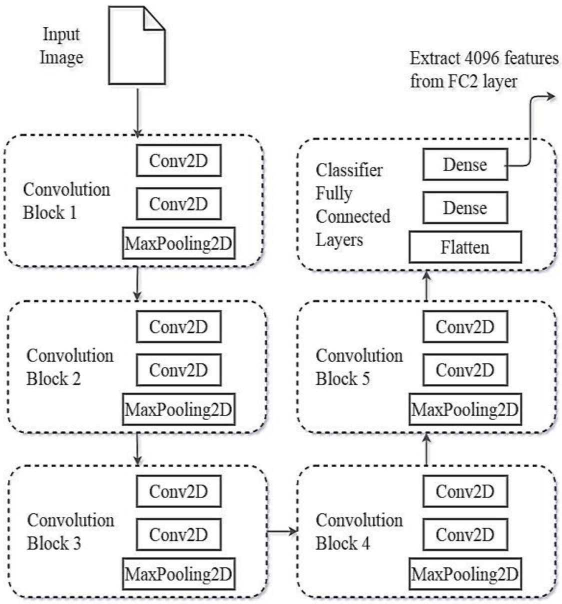


Figure 2: Working Deep Belief Networks



Here is the sigmoid belief net learning rule: The leaf nodes may be used to create an unbiased example, which allows us to examine which data the network believes in and which data it does not. In situations when there are a large number of plausible hidden causes, estimating the posterior distribution might be problematic. A small sample, even if it is insignificant, can be difficult to obtain from the back. So, how can we train sophisticated belief networks with millions of parameters when we have millions of variables?

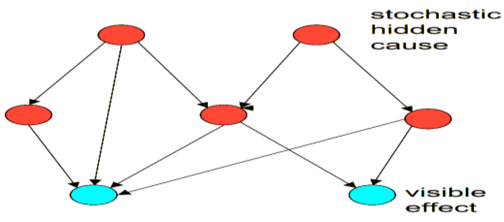


Figure 3: Working Deep Belief Networks

In order to gain insight into the hidden state distribution, we need to collect an unbiased sample of observable data. Do your best to make each unit's sampled binary states more likely to come from the sampled binary states of its parents.

Working of Proposed framework: This framework employs the properties of a deep CNN model that has been pre-trained for it. Pre-trained CNN models were used to create new features that were then used in the examples below in Figure 4.

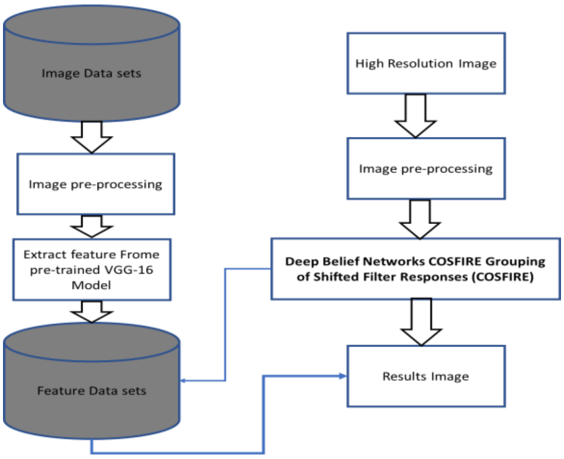


Figure 4: Methodology using features from VGG16 model

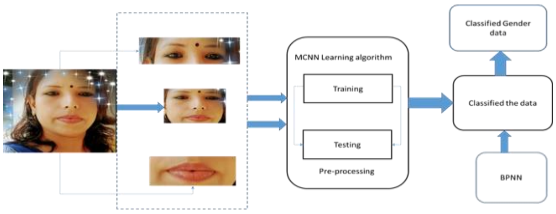


Figure 5: Proposed Framework working

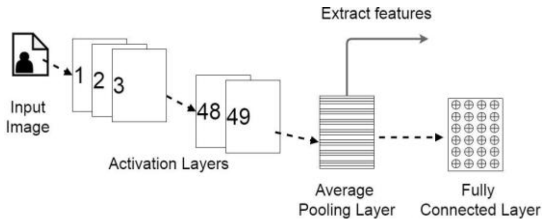


Figure 6: Feature extraction from VGG 16 model.

In the approach described above, the VGG16 model is employed to generate the results. As shown in Figure 5, a fully connected (FC2) layer is utilised to retrieve 4096 features from the model, which were learned through experimentation. It is the second to final layer in the model, and it is made up of FCs. Different pre-trained models, such as ResNet50 and Inception V3, can be utilised to generate a solution that is comparable to the original. ResNet50 is a deep CNN model that is commonly used and is based on Residual Networks. ResNet50 is a 50-layer, five-block structure with a total of 50 blocks. Each step is comprised of convolution and identity blocks. In addition, each block contains three convolutional layers, which are described below. Using a ResNet50 model, we were able to discover 2048 new features in the average pooling layer, which we then investigated further. The feature extraction process of the ResNet model is illustrated graphically. Inception V3, a 42-layer CNN developed by Google's GoogleNet family, is the most latest deep CNN to be released. The average pool layer in Inception V3 creates 2048 units, which is the same as ResNet50's.
Following are some examples of how the proposed approach implementation is performed through the use of features from theVGG16 model, as demonstrated in the methods presented in the following sections. It is possible to perform an equivalent implementation using the ResNet50 and InceptionV3 models, which incorporate the best features of all of the previously trained models in one package. It is done for all photos, including the query image, in order to extract the features from each one of the photographs.

Implementation And Result

Hardware and Software Requirements: Full-bezel 14-inch IPS touchscreen on x360 Touchscreen 2-in-1. 10th-generation Intel Core i7-10510U laptop with 512GB SSD utilized Python. Windows 10 Home 64-bit OS. CPUs: The fundamental clock speed may be boosted to 4.9 GHz owing to Intel's Turbo Boost Technology. This system has HD audio and Iris Plus graphics. HP manufactures HD TrueVision cameras. NumPy, Pandas, SciPy, PyTorch, Plotly, TensorFlow, Keras, and OpenCV-python were used.

DataSet: In this paper we have to used celeba [35], FERET [36], LFW [37] ,and UTK [38] datasets for experimental.

Implementation

Figure 8: Examples from the datasets Celeb, FEET, LFW, and UTK as a basis for this discussion

Result

Table 1. New model comparison using LFW dataset

	LFW		
	Recall (FN)	Precision(FP)	Accuracy
Inception V3 [30]	51	40	79
VGG16 [31]	61	60	70
ResNet 50 [32]	65	60	68
EfficentNet [33]	71	78	72
HyperFace [34]	92	91	87
HF-ResNet [34]	84	86	93
Proposed	97	98	99

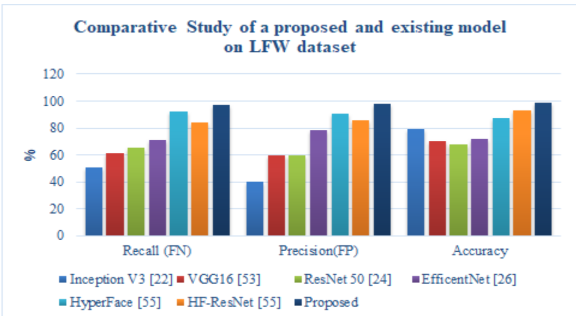


Figure 9: New model comparison using LFW dataset

Table 2. New model comparison using UTK dataset

	UTK Face		
	Recall (FN)	Precision(FP)	Accuracy
Inception V3 [30]	64	70	61
VGG16 [31]	49	60	58
ResNet 50 [32]	40	60	68
EfficentNet [33]	80	79	82
HyperFace [34]	84	86	93
HF-ResNet [34]	88	87	90
Proposed	96	97	98

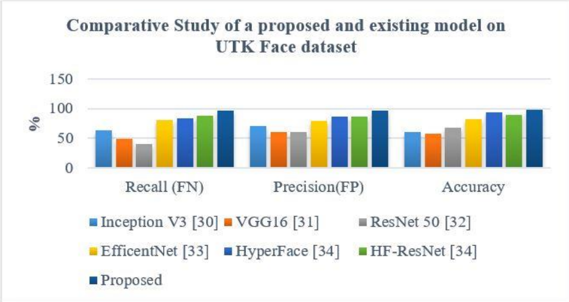


Figure 10: New model comparison using UTK dataset

Table 3. New model comparison using CELEBA dataset

	CELEBA		
	Recall (FN)	Precision(FP)	Accuracy
Inception V3 [30]	67	71	74
VGG16 [31]	68	70	71
ResNet 50 [32]	65	60	68
EfficentNet [33]	70	72	78
HyperFace [34]	75	72	80
HF-ResNet [34]	78	81	86
Proposed	96	98	99

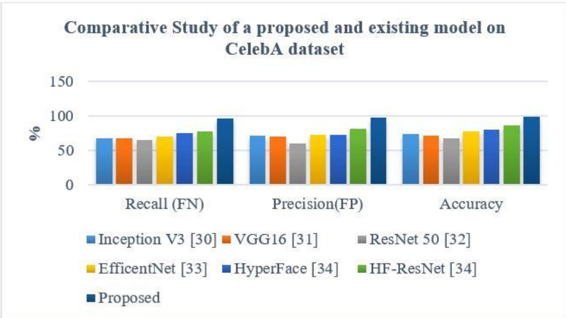


Figure 11: New model comparison using CELEBA dataset

Table 4. New model comparison using FERET dataset

	FERET		
	Recall (FN)	Precision(FP)	Accuracy
Inception V3 [30]	62	69	71
VGG16 [31]	52	59	61
ResNet 50 [32]	50	52	56
EfficentNet [33]	68	62	76
HyperFace [34]	80	78	84
HF-ResNet [34]	81	84	91
Proposed	97	95	98

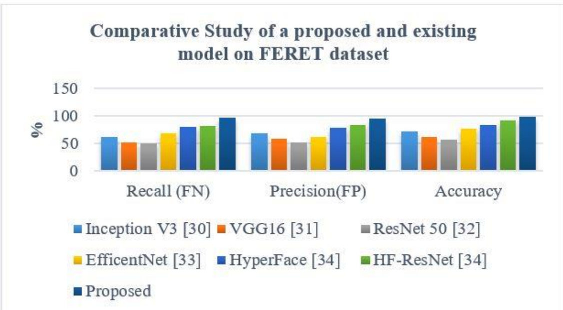


Figure 12: New model comparison using FERET dataset

Conclusion

Gender categorization research has the potential to improve several applications such as computer vision systems, biometric identification systems, credit card verification systems, visual surveillance systems, data gathering and security systems, and more. Several disciplines, such as machine learning, image processing, and human-computer interaction, have gained significant advantages from the remarkable discoveries in this domain.

The study employs widely used datasets to evaluate the performance of the CNN, VGG 16, Resnet50, inception v3, and EfficientNet models. Resnet 152 outperforms other models in terms of outcomes. These Resnet 152 models outperform state-of-the-art alternatives by 9 percentage points. Furthermore, our suggested models are more proficient than their predecessors in handling outliers.

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