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Gender Classification: An Integrated Analysis of Multimodal Biometric Data Using Deep Learning Techniques

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A B S T R A C T

With the tremendous growth in the modern technological e-resources and e-security in the recent years, personal identification and authentication has become an important and demanding technique. The biometric systems are considered to be most promising tools till date. The proposed work focuses on multimodal biometrics data-based gender classification using deep learning techniques. Now days, the convolutional neural networks (CNN) have seen great success in analyzing the images into the respective classes. The proposed system structured on CNNs, which is used to extract the features and classify images using the softmax classifier. Two biometric modalities Face and Handwritten Signatures were used for classifying the gender of human. To check the robustness of the algorithm, two CNN models were combined for Face and handwritten signature. The dataset consists total in-house of 7020 images which comprised of 3510 face images and 3510 signature samples, collected from 351 male (193) and female (158) volunteers. The obtained results in the proposed method outperformed the existing works using conventional state-of-the art techniques.

Keywords: *Face, Multimodal Biometrics, Offline handwritten Signature, Transfer Learning*

Introduction

In today's world, personal authentication and authorization using multimodal biometric data has eased to identify the individual more accurately. The usage of biometric systems become inevitable in many areas and widely used in mobile phones, document verifications, airports and identity cards and so on. In many traditional identification cases such as maintain passwords and smart cards, the biometrics have removed hurdles of using these methods [1]. Biometrics is the science of identifying the individuals based on biological and soft traits [2]. Biological traits are categorized into types: Physical and behavioral characters such as (Physical: Face, Fingerprint, hand geometry and ear), (Behavioral: Handwritten Signature, Key stroke and Gait) and soft traits are Gender, Age, Hair color, ethnicity and nationality [3]. It is one of the rapidly emerging and active research area in variety of applications [1], like court-of-law, e-KYC, Health care [4][5], and many more.

Basically, the biometric recognized systems designed into four modules: Image Acquisition, pre-processing module, feature extraction, Classification or matching module. Biometric systems are existing in two types: Unimodal and multimodal biometric systems. Unimodal biometrics are used to identify the person using single biometric data like face recognition [6], fingerprint recognition [7] and iris recognition [8] and so on. These systems also may encounter in situations like degraded image, noisy sensor data and lack of information, inter-class variability and so on. Relatively, with the outbreaks in medical emergencies, usage of materials like face masks, protective hand gloves will block the face and fingerprint identification which makes difficult to recognize [9]. As a solution, the development of biometric systems is upgrading constantly from adopting the multimodal over unimodal biometrics. Multimodal biometrics are said to be combining the one biometric trait with another biometric trait to recognize the user. In multimodal biometric systems, the careful designing of the algorithm and fusion of data or features will lead to better enhancement and improvement in recognition rate. Many research works have been carried on fusion of biometrics like, face and fingerprint recognition, palm print and fingerprint recognition and many are succeeded.

Face and Offline Handwritten Signature are the two biometrics which plays a vital role in health care, banking and in the court of law. These are more representative and easily collectable biometrics without active cooperation of the person [10]. Face and signatures are universally accepted biometric features, which enables the discriminant features and minimizes the search space. Gender classification is a binary classification (M or F) problem which conveys observable characters from human beings to distinguish between male and female class. It is a demographic characteristic of the person and finds very informative data in the application areas like human computer interaction, biometric-based access control, target advertisement and in surveillance [11]. The development of multimodal biometric face and handwritten signature images-based gender classification system is relatively having less attention among researchers. However, several researchers have carried some of the works which relies on physiological biometric characters using machine learning and deep learning techniques.

Recently, Deep learning techniques enormously used in the gender classification systems, which made considerable impact among biometrics [12-14]. Machine learning algorithms have particularly associated with the feature computation. Some feature extractions techniques may fail to identify the same biometric data with different datasets. To overcome these limitations deep learning models were introduced, it can extract the features from the raw data

[15]. In view of this, the proposed study aims to analyze the use of deep learning algorithms (CNNs) in classifying a person from two biometric traits, Face and Offline Handwritten Signature images. These traits are most extrinsic characters, naturally found, unique among individuals and highly precise in nature. Gender information from these data could easily captured and it will improvise the recognition accuracy. To the best of our knowledge, there are a lesser number of works have been carried on gender classification using face and handwritten signature. In the proposed work, the fusion of multimodal biometrics as well as fusion of transfer learning models for classification is explored.

The rest of the proposed work organized as follows: section 2 provides an overview of the previous works towards gender classification, section 3 explains the proposed model, section 4 discussed the experimental setup and results and in last section conclusion and feature scope of the work is been discussed.

Related Work

In the field of computer vision and pattern recognition, Multimodal biometric data analysis for gender classification is a challenging research work since fusion of biometrics deals with variety of characteristics, the identification is based on intrinsic feature i.e., gender, hair color, age and skin color etc. In the existing literature, there are comprehensive research works devoted to the gender classification.

In [13], Authors used face, fingerprint and iris images for multimodal biometric data analysis using machine learning algorithms. Extensive experiments were conducted on SDUMLA-HMT and KVK-Multimodal datasets, for feature computation 4 feature techniques were utilized like, Binary Statistical Image Features (BSIF), Gabor Wavelet, Multi-Block Local Binary Pattern (MB-LBP) and Segmentation based Fractal Texture Analysis (SFTA). All the features were combined using feature level fusion and trained using three machine learning algorithms viz. K-Nearest Neighbor, Support Vector Machine, and Decision tree. Further, Classifiers also synthesized and outperformed a classification accuracy of 99.4%. In [14], the same authors have analyzed the multimodal biometrics for gender classification using same dataset, in this work, MB-LBP and BSIF features were extracted from each dataset, later the features are fused using feature level fusion method and trained to Linear Discriminant Analysis, SVM and KNN classifiers. They achieved a classification accuracy of 99.8% on SVM, 96.2 % on KNN and 91.4% on LDA algorithms.

In 2015, G. Prabhu and Poornima S. [16] have proposed a work on advantages of minimizing the search space in gender classification using multimodal biometrics. To determine the gender details three biometric modalities were used viz. fingerprints, palmprints and hand geometry. A dataset small dataset comprised of 40 people (20 male and 20 female) were participated. The Palmprints and fingerprints features were extracted using Singular Value Decomposition along with 6 level Discrete Wavelet Transform. The combination of two features trained to K-Nearest Neighbor Classifier which obtained an optimum classification rate of 88.28%. Whereas, for Hand geometry, Zernike moments and Fourier descriptors were used to extract the features. Fusion of these two features performed using score level fusion and Linear Discriminant Analysis (LDA), which obtained an accuracy of 98%.

Dogucan Yaman et. al., [17] have proposed end-to-end multimodal deep learning framework for the age and gender classification, using profile face and ear images of three different standard datasets UND-F, UND-J2 and FERET. Features were extracted using VGG16 and ResNet50 models. Different fusion strategies were employed to discriminate the feature space like data, score and feature level fusion. A gender classification accuracy of 99.11%, 100% and 99.79% were achieved on FERET, UND-F and UND-J2 dataset.

Guangpeng Zhang and Yunhong Wang [18] have proposed an automatic gender classification using face profiles and ear images of UND-F dataset. Hierarchical and discriminative bag of features techniques were used to extract powerful features, and classified using support vector classification (SVC) with histogram intersection kernel. Later fusion of features on multimodalities based on Bayesian analysis has achieved a classification accuracy of 97.65%.

In [19], gender classification experiments are presented using face-ocular images. Uniform Local Binary Pattern (ULBP) technique is utilized to extract the features. This is the first study viz. considering the fusion of face and ocular biometrics using hybrid multimodal-scheme. Efficient feature sets selected using backtracking search algorithm (BSA) and to investigate the effect of multimodal data score and feature-level fusion methods were employed. In this work CASIA-Iris-Distance and MBGC multimodal biometric databases are considered and trained to SVM classifier which achieved a prediction accuracy of 88±94% with Total error rate of 5.85±0.40.

In [20], authors have proposed a novel on age and gender classification using Gated Residual Attention Network (GRA_Net) which is an improved version of Residual Attention Network. Experiments are carried on five publicly available datasets namely FG_NET, Wikipedia, AFAD, UTKFace and AdienceDB. An accuracy of 99.2% for gender classification and 93.2% for age classification obtained.

Based on the observed previous works, it is noted that the deep learning techniques over machine learning techniques have outperformed significantly good results and there are few studies have used fusion of models on physical and behavioral biometric data. The proposed work is aims to develop a deep model framework for multimodal biometric data analysis for gender classification using face and handwritten signature images.

Motivation and Contributions

Biometric systems have used in wide range of applications such as access control, identity authentication and surveillance. It is important that gender information in demographic search and target advertisements, acts as informative clue which can be used in many real-world sectors. Similarly, gender is a soft-biometric trait that enhances the recognition performance. Though gender classification is challenged by many factors like low clarity, falsification of inputs etc. Earlier works on gender classification system, have suggested that it can provide new insights of findings. Also, in case of identification of individuals the key comparison among equal female and male images, it can drastically reduce the search time in large dataset. With this motivation the proposed work focused on gender classification system for face and handwritten signature images using deep learning models.

The key contributions of the proposed work:

1. Creation of Multimodal Biometric database.
2. Multimodal biometric data fusion of Face and Handwritten Signature Images.
3. Analyzing the Unimodal and Multimodal biometric Gender classification using deep learning models.
4. Evaluate and analyze the performance of the proposed work with comparing the existing work.

Proposed Methodology

In this study, CNN based multimodal biometric-based gender classification using face and handwritten signature is proposed. The general methodology of the proposed work is demonstrated in the figure 1.

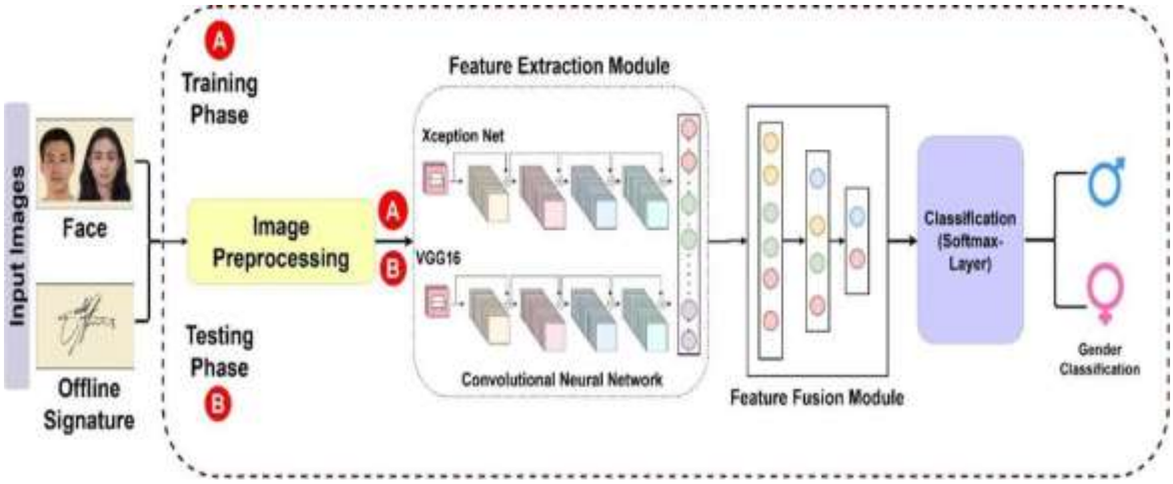


Figure 1. Workflow diagram of proposed methodology

In this study, combination of two channel Convolutional Neural Network deep model feature fusion framework is proposed as shown in the figure 1. The methodology divided into four modules namely Image preprocessing, feature extraction modules, feature fusion module and classification part. In the preprocessing module the acquired images are normalized into pre-defined image size and unwanted distortions were removed to enhance image quality. The images are fetched into feature extraction module and convoluted into two pre-trained transfer learning models, the features of biometric images are extracted into multi-layer convolution and max-pooling layer. In the next step, the extracted features of both models are combined using feature fusion layer. Later, the obtained the weights and features of face and signatures from the feature extraction are pass through the SoftMax layer and then flattened the features together [9]. The fully connected layer is used for classification of images.

Transfer Learning models

In recent years, Transfer learning models have been effective in varieties of applications like computer vision, Natural Language Processing and Data Mining. Even in the smaller dataset these models can improve the performance.

VGG16

VGG16 is one of the convolutional neural networks proposed by Visual Geometry Group of Oxford University in 2014. Karen Simonyan and Andrew Zisserman have firstly introduced this convolutional neural network in their work entitle as “Very Deep Convolutional Neural Network for Large-Scale Image Recognition” [21].

VGG16 is composed of 16 layers in total, which includes 13 convolutional layers and 3 fully connected layers. The stack of convolution layer has 3x3 convolutional filter i.e., small receptive field with small stride and allowing the network to learn complex hierarchical features the depth increases from 64 to 512 layers followed by ReLU activation. Noteworthy are 5 max-pooling layers with 2x2 pool size and stride 2 provides spatial reduction. 3 fully connected layers in the last which produces the final output. The below illustrates the general architectural diagram of VGG16 model.

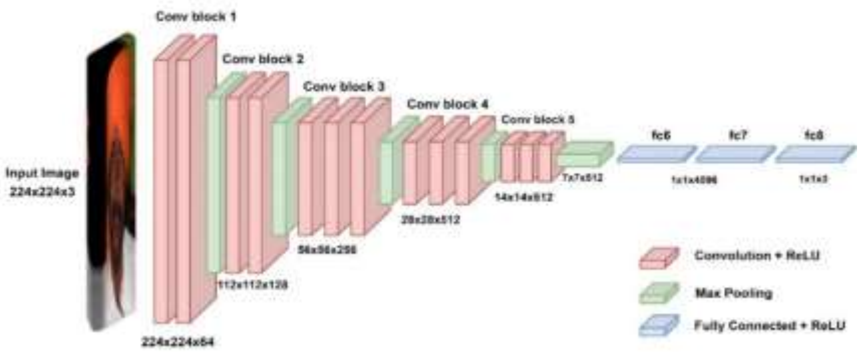


Figure 2. General Architecture of the VGG16 Model

Xception Model

Xception is a firstly introduced by Francois Chollet in their paper entitled as “Xception: Deep Learning with Depthwise Separable Convolutions” [22]. It is deep convolutional neural network inspired by Inception architecture [23]. Xception stands for “Extreme Inception”, the architecture has 36 convolutional layers for feature extraction, these layers are structured into 14 modules. The Xception involves depth wise and point wise convolution. This architecture significantly reduces computational complexity and the number of parameters while maintaining expressive power. The network structure is organized into an entry flow, middle flow and exit flow, as illustrated in the Figure 4. Xception’s efficiency and adaptability is suitable in varieties of image classification and computer vision problems.

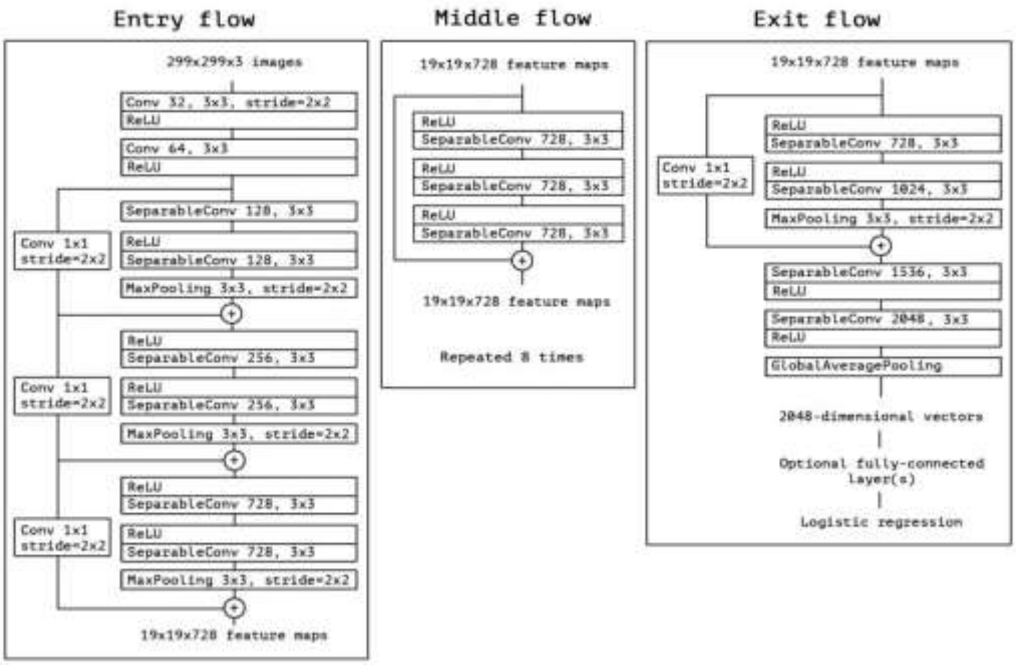


Figure 3. Network structure of Xception Net model

Feature Fusion Module

Feature computation is important part in the multimodal biometric data analysis, where each model extracts number of dominant features. Combining the feature vectors using feature-fusion techniques enhances the image classification. In this proposed work, Hybrid deep features-based feature-fusion techniques is employed. The below equation illustrates feature fusion of the two models.

$$FF = f_{vgg16} + f_{xception} \qquad (1)$$

Experimental Results and Discussion

This section discusses the dataset used, experimental results and comparative analysis of proposed work with existing work. Subsequently, performance evaluation metrics are illustrated to highlight the analyses of the proposed work.

- **Dataset Description**

a. Face Dataset

The Face Dataset was created as part of the proposed work. The dataset consists of 3510 face images of 351 subjects, male (193) and female (158) volunteers with their varying ages from 18 to 65 year.

- The face images are collected using Cannon EOS 1300D DSLR camera.
- The photos were captured in day and night lighting with natural expression and usual profile face position.
- From each individual 10 samples were collected with minimal head movements.
- The images are in 5184 x 3456 dimensions and 72 DPI and saved colour images with .jpg format.
- The below figure 5 shows the collected face samples.

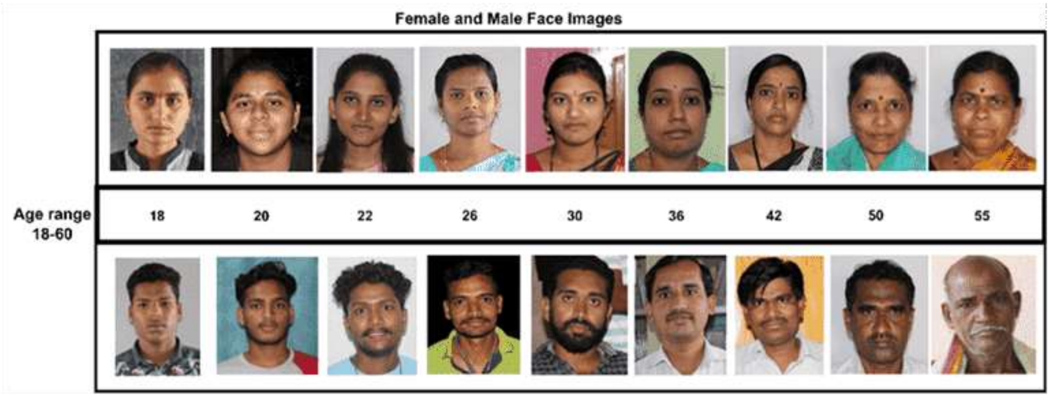


Figure 4. Collected Face image samples

b. Offline Handwritten Signature Dataset

The signatures are collected from 351 subjects with same individuals who were participated in face dataset collection.

- All the individual who had knowledge of English and other regional languages, have been educated the purpose of collecting the signature samples.
- 10 samples were collected from each individual on a A4 white sheet using blue and black colored ball pen.
- The signature samples are been scanned using EPSON DS1630 colour scanner with 300 DPI.
- The samples are in multilingual scripts of Kannada, Hindi, English and Marathi.
- The below figure 6. shows the collected samples of offline handwritten signature dataset.

Figure 5. Collected offline handwritten signature samples

Implementation setup

The proposed work is implemented using Jupyter Notebook web-based interactive platform of Anaconda Python IDE. Tensorflow keras python library are also used to analyze the data.

Results

In this work, VGG16 and XceptionNet, which are well known deep neural network architectures are used to perform gender classification from face and handwritten signature biometric modalities. Table 1. Shows the dataset split into 70% for training, 20% for validating and 10% for testing. At first, the networks were initialized with the weights of pretrained network models, which was trained on ImageNet Dataset. Further, the networks are fine-tuned on datasets to classify the gender. In the training, the initial learning rate selected as 0.001, with 20 epochs and Adam optimizer is employed throughout the experimentation. While the batch size is 32 chosen for both unimodal and multimodal representation. The Max pooling and ReLU activation function is utilized in both networks, also the dropout with 0.5 drop rate is used after each fully-connected layer except output layer. The final output layer has SoftMax activation function with cross-entropy loss function to prevent performance degradation of gender classification during the training.

The algorithmic steps are as follows:

Input: Multimodal biometric images.

Output: Gender classification from multimodal biometric images.

Step 1: Input the images from the dataset.

Step 2: Normalize the image into 224x224x3 size.

Step 3: VGG16 and XceptionNet model for Feature extraction.

Step 4: Feature fusion and classification using both transfer learning models.

Step 5: Feature map is trained and tested for validation.

Step 6: Analysed performance metric evaluation to test the dataset.

Table 1: Data Split into ratio 70:20:10

Datasets	Total	Train (70%)	Validation (20%)	Test (10%)
Face Images	3510	2457	702	351
Offline Handwritten Signature Images	3510	2457	702	351
Combined Dataset	7020	4914	1404	702

- **Gender Classification Results**

The unimodal and multimodal biometric based gender classification results are shown in the Table 2 & 3, also the performance evaluation results are shown in Table 4. All these results are obtained on two datasets i.e., face and handwritten signatures. Three kinds experiments were carried on, firstly unimodal biometric based gender classification using individual models. Secondly, combining the features extracted on unimodal into both models and train. Third, combining both dataset and train the individual model, later the extracted features are fused and trained using CNN. The best gender classification results which are 98.86% for combination of models VGG16+XceptionNet using Face dataset, 91.31% for combining the dataset Face + Signature using VGG16+XceptionNet and finally, combination of models using signature dataset have obtained 88.03% respectively. The Figure 8 illustrates the test data results confusion matrix of unimodal biometrics, Figure 9 followed by confusion matrix of multimodal biometrics and Figure 10. confusion matrix of both dataset with both models.

Table 2. Gender classification results using different modalities

Models	Face	Handwritten Signature
	Test Accuracy	**Test Accuracy**
VGG16	98.29%	82.62%
XceptionNet	92.39%	74.29%
VGG16+XceptionNet	98.86%	88.03%

Table 3. Gender classification results using different modalities

Datasets	VGG16	XceptionNet
	Test Accuracy	**Test Accuracy**
Both (F+H)	82.33%	82.33%
Both (F+H) + both (VGG16+XceptionNet)	91.31%	

Note: F= Face dataset, H= Handwritten Signature*

- **Performance Evaluation Results:** The performance evaluation is used to understand how well the proposed model is performed based on the metrics values on given dataset. The metrics used in this study are listed below.

- **Accuracy:** is determined using correct values to the total values.

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{No.of\ correctly\ predicted\ values}}{\boldsymbol{total\ no.of\ values}} \qquad \textbf{(2)}$$

The terms used in the performance metrics are given below in the figure 6.

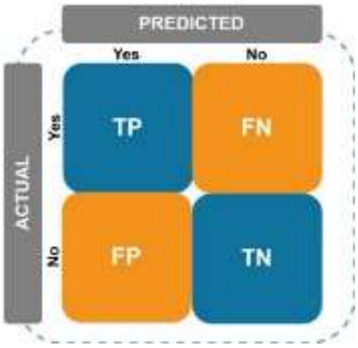


Figure 6. Terminologies of confusion matrix

- True Positive (TP): the prediction outcome is true.
- True Negative (TN): the prediction outcome is false.
- False Positive (FP): the prediction outcomes are true.
- False Negative (FN): the prediction outcomes are false.

- **Precision:** This metric determines the accuracy constraints. It can be measured as the proportion of true positive predictions to total positive predictions.

$$\boldsymbol{Precision} = \frac{TP}{(TP+FP)} \qquad (3)$$

- **Recall**: It focuses on determining the proportion of real positives that were misidentified. The following formula can be used to calculate recall:

$$\boldsymbol{Recall} = \frac{TP}{TP+FN} \qquad (4)$$

- **F1-Scores:** It is a form of composite score that includes both precision and recall. As a result, the F1 score can be calculated as the harmonic mean of precision and recall, with equal weight given to each.

$$\boldsymbol{F1 - Scores} = 2 * \frac{precision*recall}{precision+recall} \qquad (5)$$

Table 4: Performance evaluation results of the proposed method

Datasets	***Models***	***Precision***	***Recall***	***F1-Scores***	***Accuracy***
Face	VGG16	0.98	0.98	0.98	0.9829
	XceptionNet	0.95	0.91	0.93	0.9230
	VGG16+XceptionNet	0.99	0.98	0.99	0.9886
Handwritten Signature	VGG16	0.87	0.83	0.82	0.8262
	XceptionNet	0.75	0.84	0.79	0.7492
	VGG16+XceptionNet	0.87	0.92	0.89	0.8803
Face + Handwritten Signature	VGG16	0.86	0.84	0.82	0.8233
	XceptionNet	0.83	0.82	0.82	0.8233
	VGG16+XceptionNet	0.91	0.91	0.91	0.9131

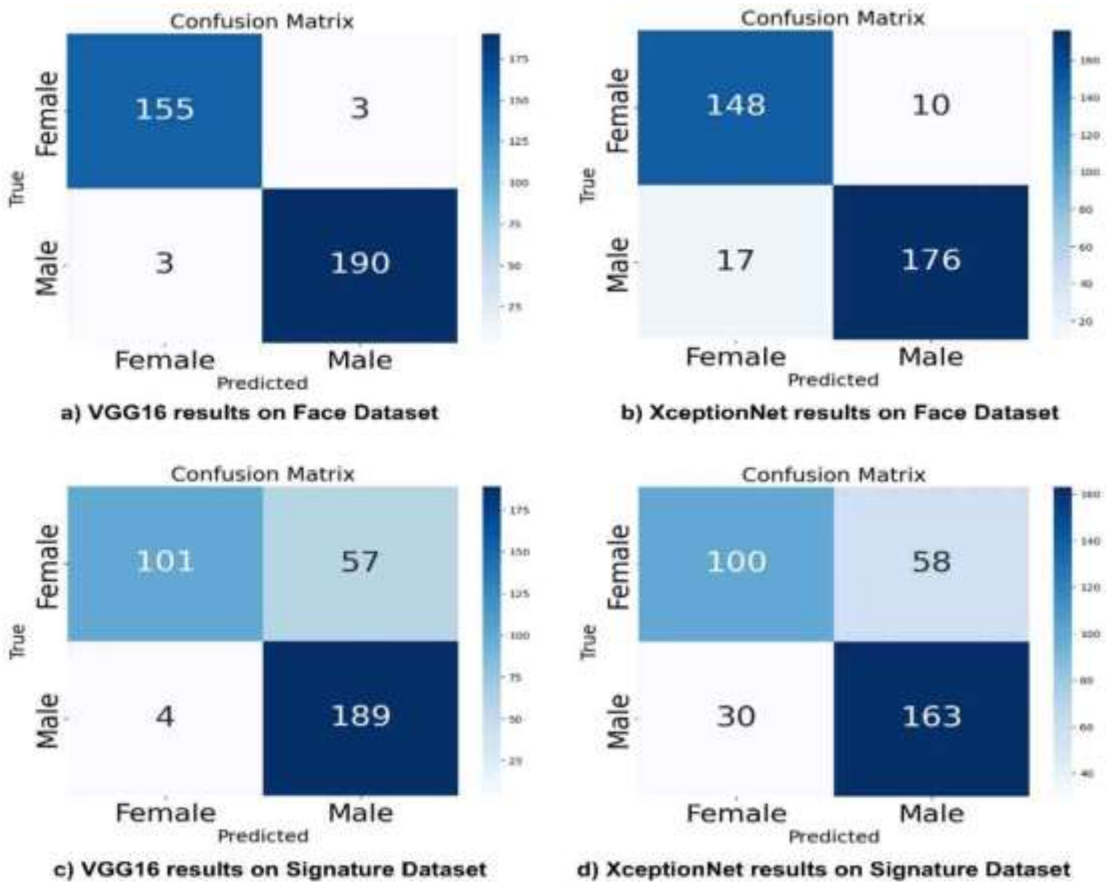


Figure 7. Confusion Matrix of test data results of Face and Handwritten Signature Dataset

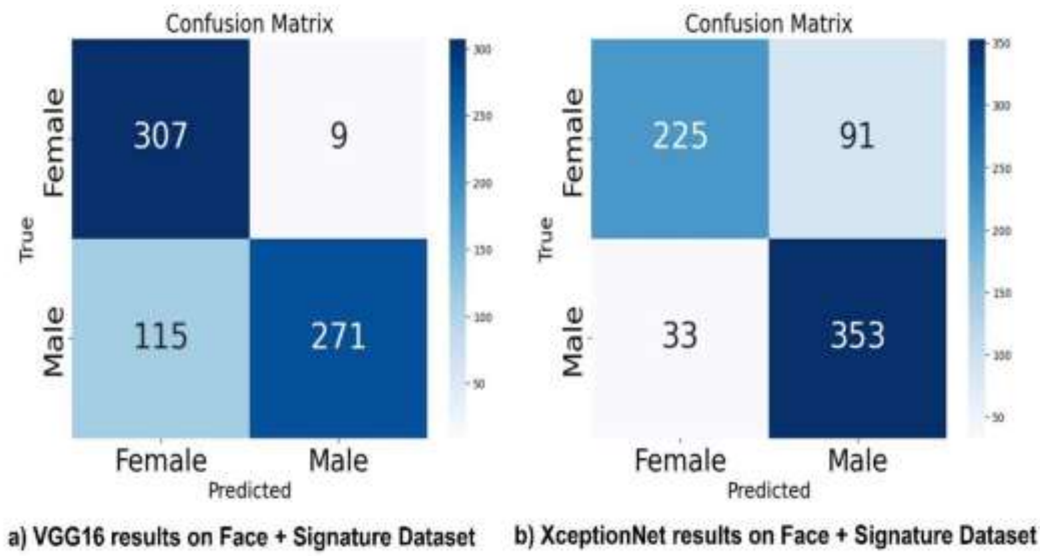
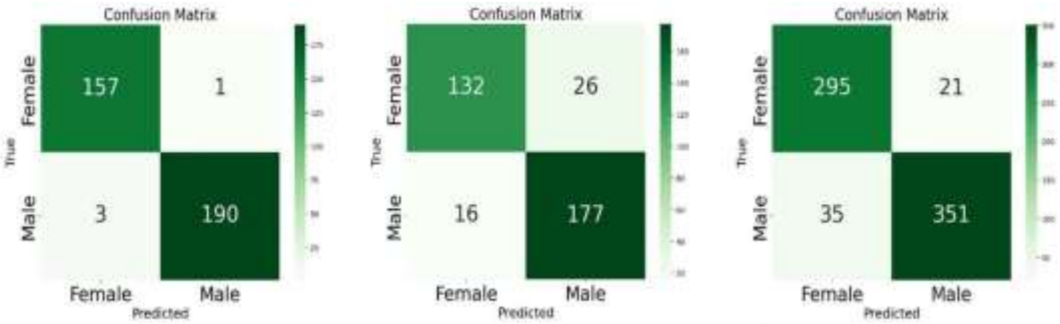


Figure 8. Confusion Matrix of test data results of Both Dataset



a) Test Results of combined model using Face **b) Test Results of combined model using Handwritten Signature** **c) Test Results of combined model using Face + Handwritten Signature**

Figure 9. Test data results of multimodal biometric data

In the final analysis, it has been observed that the results produced for model fusion contribute to a greater performance rate when compared to a monomodal system.

Comparative Analysis

Table 5 provides a comparative overview of existing and proposed work. It highlights the most recent findings, feature extraction, and classification approaches employed, as well as the results obtained using multimodal biometric data for gender classification.

Table 5: Overview Comparative analysis on Gender Classification Systems

Author	**Methodology**	**Dataset**	**Classifiers**	**Results**
Shivanand S. Gornale et al. [13]	AlexNet	SDUMLA-HMT 15052 images (Face+Iris+Fingerprint)	CNN (AlexNet)	99.9%
Patil et. al [14]	MB-LBP, BSIF	SDUMLA-HMT 15052 images (Face+Iris+Fingerprint)	CNN model	99.8%
G. Prabhu and Poornima S. [16]	Singular Value Decomposition (SVD) and Discrete Wavelet Transform (DWT)	Fingerprints + Palmprints + Hand geometry 40 people (20 male and 20 female)	K-Nearest Neighbour Classifier	98%
Dogucan Yaman et. al [17]	ResNet-50 VGG16	FERET, UND-F and UND-J2 datasets	VGG16 and ResNet-50	67.59% for FERET 66.44% for ResNet-50 99.11% for combined both models
Guangpeng zhang and Yunhong Wang [18]	Hierarchical and Discriminative bag of features	UND-F dataset	Support Vector Classification	97.65%
Maryam Eskandari and Omid Sharifi [19]	Uniform LBP and Backtracking search algorithm (BSA)	CASIA-Iris and MBGC multimodal biometrics	Support Vector Machine	94%
Avishek Garain et. al [20]	GRA_Net (Gated Residual Attention Network)	FG-NET, Wikipedia, AFAD, UTK-Face and AdienceDB	CNN	99.2%
Proposed Method	**VGG16** **XceptionNet**	**3510 Face images,** **3510 Offline Signature images,** **7020 Face +Offline Signature images**	**VGG16 and XceptionNet**	**88.03% for Handwritten Signature, 98.86% for Face images** **91.31% for both dataset**

However, it was observed that the proposed method, which uses a combination of two transfer learning methods, achieved significantly better recognition results on two datasets: Face and Offline Handwritten Signature Datasets.

Conclusion

In this paper, we propose a multimodal biometric data analysis for gender classification using deep learning techniques. Gender classification systems are in demand to address the issues of security, document verification, and criminal investigations. Our approach aims to classify an individual's data based on their physical and behavioral biometrics. We employ two different transfer learning methods for domain adaptation, namely the VGG16 and XceptionNet models. To make the features more distinctive, we employ a combination of feature fusion from the two models. We analyze each biometric data using the models and achieved significantly good results. Finally, our proposed method explores the importance of profile face images and offline handwritten signature images.

Conflict of Interest

Authors declare that there is no conflict of interest.

References

[1] Nayak, J. S., & Indiramma, M. (2022). An approach to enhance age invariant face recognition performance based on gender classification. *Journal of King Saud University -Computer and Information Sciences*, *34*(8), 5183–5191. https://doi.org/10.1016/j.jksuci.2021.01.005

[2] Gornale, S. S., Kumar, S., Patil, A., & Hiremath, P. S. (2021). Behavioral Biometric Data Analysis for Gender Classification Using Feature Fusion and Machine Learning. Frontiers in Robotics and AI, 8. https://doi.org/10.3389/frobt.2021.685966

[3] Gornale, S. S., Kumar, S., Siddalingappa, R., & Mane, A. (2022). Gender Classification Based on Online Signature Features using Machine Learning Techniques. International Journal of Intelligent Systems and Applications in Engineering, 10(2), 260–268.

[4] Gornale, S., Kumar, S., Siddalingappa, R., & Hiremath, P. S. (2022). Survey on Handwritten Signature Biometric Data Analysis for Assessment of Neurological Disorder using Machine Learning Techniques. Transactions on Machine Learning and Artificial Intelligence, 10(2), 27–60. https://doi.org/10.14738/tmlai.102.12210

[5] Gornale, S. S., Kumar, S., & Hiremath, P. S. (2021). Handwritten Signature Biometric Data Analysis for Personality Prediction System Using Machine Learning Techniques. Transactions on Machine Learning and Artificial Intelligence, 9(5), 1–22. https://doi.org/10.14738/tmlai.95.10808

[6] Shekar, B. H., Sharmila Kumari, M., Mestetskiy, L. M., & Dyshkant, N. F. (2011). Face recognition using kernel entropy component analysis. Neurocomputing, 74(6), 1053–1057. https://doi.org/10.1016/j.neucom.2010.10.012

[7] R, K., Patil, A., & Gornale, S. (2019). Fusion of Features and Synthesis Classifiers for Gender Classification using Fingerprints. International Journal of Computer Sciences and Engineering, 7(5), 526–533. https://doi.org/10.26438/ijcse/v7i5.526533

[8] Shekar, B. H., Bhat, S. S., & Maysuradze, A. (2019). Reliability index for iris code matching in iris recognition systems. In International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives (Vol. 42, pp. 197–202). International Society for Photogrammetry and Remote Sensing. https://doi.org/10.5194/isprs-archives-XLII-2-W12-197-2019

[9] Wang, Y., Shi, D., & Zhou, W. (2022). Convolutional Neural Network Approach Based on Multimodal Biometric System with Fusion of Face and Finger Vein Features. Sensors, 22(16). https://doi.org/10.3390/s22166039

[10] Medjahed, C., Rahmoun, A., Charrier, C., & Mezzoudj, F. (2022). A deep learning-based multimodal biometric system using score fusion. IAES International Journal of Artificial Intelligence, 11(1), 65–80. https://doi.org/10.11591/ijai.v11.i1.pp65-80

[11] Dargan, S., & Kumar, M. (2021). Gender classification and writer identification system based on handwriting in gurumukhi script. In Proceedings - IEEE 2021 International Conference on Computing, Communication, and Intelligent Systems, ICCCIS 2021 (pp. 388–393). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/ICCCIS51004.2021.9397201

[12] Kumar, S., Gornale, S. S., & Siddalingappa, R. (2023). Gender Classification from Behavioural Biometric Data using Convolutional Neural Network (pp. 646–659). https://doi.org/10.2991/978-94-6463-196-8_49

[13] Gornale, S. S., Patil, A., & Kruthi, R. (2019). Multimodal biometrics data based gender classification using machine vision. International Journal of Innovative Technology and Exploring Engineering, 8(11), 1356–1363. https://doi.org/10.35940/ijitee.J9673.0981119

[14] Patil, A., Kruthi, R., & Gornale, S. (2019). Analysis of Multi-modal Biometrics System for Gender Classification Using Face, Iris and Fingerprint Images. International Journal of Image, Graphics and Signal Processing, 11(5), 34–43. https://doi.org/10.5815/ijigsp.2019.05.04

[15] Alay, N., & Al-Baity, H. H. (2020). Deep learning approach for multimodal biometric recognition system based on fusion of iris, face, and finger vein traits. Sensors (Switzerland), 20(19), 1–17. https://doi.org/10.3390/s20195523

[16] Prabhu, G., & Poornima, S. (2015). Minimize search time through gender classification from multimodal biometrics. In Procedia Computer Science (Vol. 50, pp. 289–294). Elsevier B.V. https://doi.org/10.1016/j.procs.2015.04.046

[17] Yaman, D., Eyiokur, F. I., & Ekenel, H. K. (2022). Multimodal soft biometrics: combining ear and face biometrics for age and gender classification. Multimedia Tools and Applications, 81(16), 22695–22713. https://doi.org/10.1007/s11042-021-10630-8

[18] Zhang, G., & Wang, Y. (2011). Hierarchical and discriminative bag of features for face profile and ear-based gender classification. In 2011 International Joint Conference on Biometrics, IJCB 2011. https://doi.org/10.1109/IJCB.2011.6117590

[19] Eskandari, M., & Sharifi, O. (2019). Effect of face and ocular multimodal biometric systems on gender classification. IET Biometrics, 8(4), 243–248. https://doi.org/10.1049/iet-bmt.2018.5134

[20] Garain, A., Ray, B., Singh, P. K., Ahmadian, A., Senu, N., & Sarkar, R. (2021). GRA_Net: A Deep Learning Model for Classification of Age and Gender from Facial Images. IEEE Access, 9, 85672–85689. https://doi.org/10.1109/ACCESS.2021.3085971

[21] Simonyan, K., & Zisserman, A. (2015). Very deep convolutional networks for large-scale image recognition. In 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track Proceedings. International Conference on Learning Representations, ICLR.

[22] Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017 (Vol. 2017-January, pp. 1800–1807). Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/CVPR.2017.195

[23] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., & Wojna, Z. (2016). Rethinking the Inception Architecture for Computer Vision. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition (Vol. 2016-December, pp. 2818–2826). IEEE Computer Society. https://doi.org/10.1109/CVPR.2016.308