International Journal of Academic Information Systems Research (IJAISR)
ISSN: 2643-9026
Vol. 10 Issue 2 February - 2026, Pages: 35-41

Eye Gender Classification Using Transfer Learning (VGG16) on EyeDataset

Mohammed Sabri Al-madani, Mohammed Mahdi Jarour, Samy S. Abu-Naser

Department of Information Technology,
Faculty of Engineering & Information Technology,
Al-Azhar University-Gaza, Palestine

Abstract: *Automated analysis of eye images can support a range of biomedical and computer vision applications. This paper presents a deep learning pipeline for binary classification of eye images into female eyes (0) and male eyes (1) using Eye Dataset. The proposed approach uses transfer learning with a pretrained VGG16 backbone, combined with standardized preprocessing, data augmentation, and supervised training using a fixed train/validation/test protocol. The best model is saved using checkpointing based on validation loss, then evaluated on a separated test set with class-wise and overall accuracy reporting. Experimental results demonstrate that transfer learning provides strong performance for eye-image gender classification under variations in image quality and illumination. The trained model achieved 65.67%: Test Accuracy overall test accuracy, with classwise performance detailed in the classification report.*

Keywords—*Eye Dataset, transfer learning, VGG16, CNN, binary classification, eye images, gender classification*

I. INTRODUCTION

Image-based classification using deep learning has become a fundamental paradigm in modern computer vision, driven by the remarkable success of convolutional neural networks (CNNs) in learning discriminative visual representations directly from raw image data. These models have demonstrated superior performance in a wide range of application domains, including object recognition, facial analysis, medical imaging, and biometric identification. In biomedical and biometric contexts in particular, ocular images constitute a highly informative visual modality due to their rich texture patterns, stable anatomical structure, and relative invariance compared to other facial components. As a result, eye images have been widely explored for tasks such as identity recognition, disease screening, and demographic attribute estimation.

Despite their potential, eye images acquired in real-world environments are subject to several challenges that can significantly degrade classification performance[1-4]. Variations in illumination conditions can alter the apparent contrast and color distribution of the eye region, while motion blur and defocus may obscure fine-grained texture details essential for accurate feature extraction. Furthermore, partial occlusions caused by eyelids, eyelashes, eyeglasses, or hair introduce additional noise and reduce the visibility of discriminative regions such as the iris and sclera. Background artifacts and differences in camera sensors or acquisition setups further contribute to intra-class variability, making the learning process more complex and increasing the risk of model overfitting. These factors collectively highlight the need for robust and generalizable learning frameworks capable of handling noisy and heterogeneous visual data[5-8].

In this work, we address these challenges by designing an end-to-end deep learning system for the binary classification of eye images into two categories: female eyes and male eyes. The proposed framework is implemented using a fully reproducible pipeline within the Google Colab environment, enabling efficient experimentation, transparent model development, and ease of deployment. The system integrates data preprocessing, model training, validation, and performance evaluation into a unified workflow, thereby ensuring consistency and reproducibility of results[9-10].

Rather than training a deep neural network from scratch—which typically requires very large labeled datasets and extensive computational resources—we adopt a transfer learning strategy to exploit the representational power of pretrained convolutional models learned from large-scale image corpora. By fine-tuning these pretrained feature extractors on the eye image dataset, the model benefits from previously learned low-level and mid-level visual features such as edges, contours, and texture patterns, which are transferable across domains[11-14]. This approach not only accelerates convergence during training but also enhances generalization performance, particularly in scenarios where the available training data are limited. Consequently, the proposed methodology provides an effective and scalable solution for gender classification from eye images under realistic acquisition conditions.

II. RELATED WORK

Convolutional Neural Networks (CNNs) are capable of automatically learning hierarchical feature representations from visual data, enabling them to achieve state-of-the-art performance in image classification and recognition tasks. At lower network layers, CNNs typically capture fundamental visual primitives such as edges, corners, and simple textures, while deeper layers progressively learn more abstract and task-specific patterns, including shapes and semantic structures. This hierarchical learning mechanism allows CNNs to model complex visual relationships that are difficult to design manually using traditional feature engineering techniques.

However, the effectiveness of CNNs is strongly dependent on the availability of large, well-annotated datasets. In many practical scenarios, labeled data are scarce or exhibit high variability due to differences in acquisition conditions, illumination, and subject appearance. Under such constraints, training deep networks from scratch often leads to slow convergence, unstable optimization, and a higher risk of overfitting. To address these limitations, transfer learning has become a widely adopted strategy in computer vision applications[15-18].

Transfer learning involves reusing pretrained models—such as VGG, ResNet, and EfficientNet—that have been trained on large-scale image datasets[19-22]. These pretrained backbone networks provide robust and generalizable low-level and mid-level feature representations, including edges, textures, and shape-based patterns, which are largely independent of the target application domain[23-25]. By fine-tuning these pretrained models on a new dataset, the network can efficiently adapt previously learned visual features to the specific classification task with significantly fewer training samples[26-28].

In binary classification problems, transfer learning has been shown to consistently improve both predictive performance and training stability compared to CNNs trained from scratch. The reuse of pretrained weights facilitates faster convergence, reduces sensitivity to initialization, and enhances generalization by leveraging prior visual knowledge embedded in the pretrained parameters[29-32]. Consequently, transfer learning constitutes an effective and computationally efficient solution for image classification tasks characterized by limited data availability or high intra-class variability.

III. DATASET DESCRIPTION

3.1 Dataset Structure

The Eye Dataset is organized into training and testing folders, each containing subfolders for the two classes[33-35]:

- train/femaleeyes
- train/maleeyes
- test/femaleeyes
- test/maleeyes

The notebook verifies dataset paths and counts the number of images per class to assess the dataset distribution.

Class distribution:

- female eyes: 539
- male eyes: 563
- Total images: 1,102

3.2 Train/Validation/Test Protocol

The code uses a held-out test set from the dataset's test folder. The training set is further split into training and validation subsets using train_test_split, where the validation portion is 30% of the training data[36-40].

- Train samples: 1,102
- Test samples: 603

IV. METHODOLOGY

4.1 Data Loading and Label Encoding

All training images are loaded from the train directory. Each image is assigned a numeric label[41-44]:

- Female eyes → 0
- Male eyes → 1

This label encoding supports binary learning using sigmoid output.

- Image Preprocessing

Prior to model training, all input images are subjected to a standardized preprocessing pipeline to ensure compatibility with the selected deep learning architecture and to enhance learning stability. Each eye image is resized to a fixed spatial resolution of 224 × 224 pixels, which corresponds to the expected input dimensions of the VGG16 network. This resizing operation provides uniformity across the dataset and enables efficient batch processing during training[45-48].

Following resizing, the images are converted into numerical arrays representing pixel intensity values[49-52]. These arrays are then passed through the VGG16-specific preprocessing function (preprocess_input), which performs normalization and channel-wise transformations consistent with the statistical properties of the ImageNet dataset on which VGG16 was originally trained. This step is essential to align the distribution of the input data with the pretrained feature space of the backbone network[53-56]. By ensuring consistent input scaling and normalization, the preprocessing stage reduces domain mismatch between the source (ImageNet) and target (eye image) datasets, thereby facilitating more effective feature reuse and stable gradient propagation during fine-tuning.

- Data Augmentation

To enhance model robustness and mitigate overfitting, data augmentation is applied dynamically during the training phase using an Image Data Generator[54-58]. Data augmentation introduces controlled random variations into the training samples, effectively increasing the diversity of the dataset without altering the underlying class labels. This strategy allows the model to learn invariant representations that are less sensitive to minor spatial and geometric distortions commonly encountered in real-world image acquisition scenarios[59-62].

In this study, several augmentation operations are employed to simulate realistic variations in eye image appearance, including changes in orientation, position, and scale. These transformations encourage the network to focus on discriminative anatomical and textural features rather than memorizing fixed spatial patterns. As a result, the trained model exhibits improved generalization capability when evaluated on unseen samples captured under different imaging conditions.

The applied augmentation parameters are summarized as follows:

- Rotation range: 20 degrees
- Width shift range: 0.2
- Height shift range: 0.2
- Horizontal flip: enabled
- Zoom range: 0.2

Collectively, these augmentation settings provide moderate geometric variability while preserving the semantic integrity of the eye images. This balanced configuration ensures that the generated samples remain biologically plausible and class-consistent, thereby contributing positively to the learning process[63-65].

4.4 Model Architecture (Transfer Learning with VGG16)

The proposed classification model is constructed using a transfer learning framework based on the VGG16 convolutional neural network pretrained on the ImageNet dataset. The pretrained VGG16 backbone is loaded with the parameter include_top = False, which removes the original fully connected layers designed for large-scale multi-class classification. This configuration enables the use of VGG16 exclusively as a feature extractor, producing high-level convolutional feature maps from the input eye images.

Initially, all layers of the pretrained backbone are frozen by setting their trainable attribute to False. This prevents modification of the pretrained weights during the early training stages and preserves the general visual knowledge learned from large-scale natural image data. Freezing the backbone reduces the risk of overfitting and significantly decreases the number of trainable parameters, making the model more suitable for training on relatively small datasets.

On top of the frozen convolutional base, a lightweight task-specific classification head is appended. This head is responsible for transforming the extracted feature maps into a binary output corresponding to the two target classes (female eyes and male eyes). The appended layers typically consist of a flattening or global pooling layer followed by one or more fully connected layers and a final sigmoid-activated output neuron for binary classification. This architectural design allows the model to learn discriminative class boundaries while relying on the robust visual features provided by the pretrained backbone.

By combining a deep pretrained feature extractor with a compact classification head, the proposed architecture achieves an effective balance between representational power and computational efficiency. This transfer learning approach accelerates convergence, improves classification accuracy, and enhances generalization performance compared to training a

International Journal of Academic Information Systems Research (IJAISR)
ISSN: 2643-9026
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deep CNN from scratch.

Model: "functional"

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 512)	0
dropout (Dropout)	(None, 512)	0
dense (Dense)	(None, 1)	513

Total params: 14,715,201 (56.13 MB)
Trainable params: 513 (2.00 KB)
Non-trainable params: 14,714,688 (56.13 MB)

Model: "functional_1"

Layer (type)	Output Shape	Param #
input_layer_1 (InputLayer)	(None, 224, 224, 3)	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1,792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36,928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73,856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147,584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295,168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590,080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590,080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1,180,160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2,359,808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2,359,808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
global_average_pooling2d_1 (GlobalAveragePooling2D)	(None, 512)	0
dropout_1 (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 1)	513

Total params: 14,715,201 (56.13 MB)
Trainable params: 513 (2.00 KB)
Non-trainable params: 14,714,688 (56.13 MB)

4.5 Training Configuration

- Loss: binary cross-entropy
- Optimizer: Adam
- Learning rate: 1e-4
- Batch size: 32
- Epochs: 20

4.6 Model Checkpointing (Saving the Best Model)

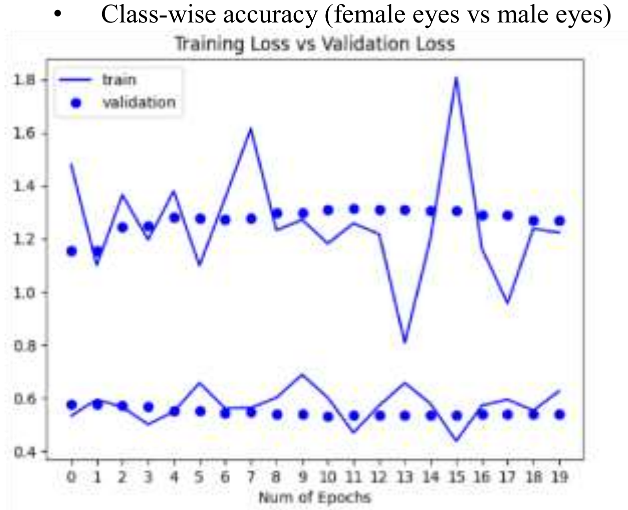
During training, ModelCheckpoint saves the best weights based on validation loss (val_loss). This ensures that the final evaluation uses the best-performing model on validation rather than the last epoch.

After training, the notebook loads the best weights before testing.

V. EXPERIMENTS AND RESULTS

5.1 Evaluation Metrics

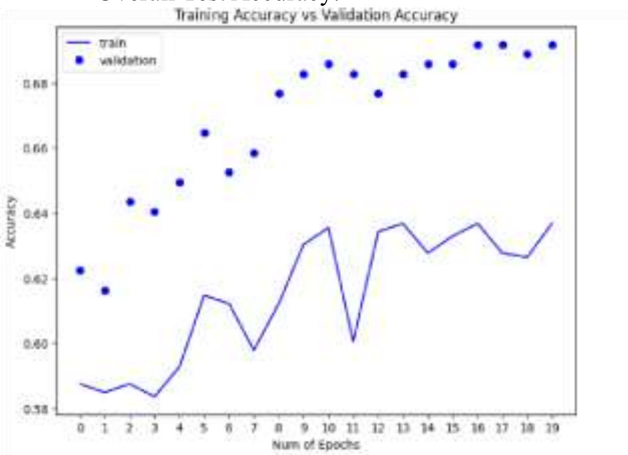
- The system is evaluated using:
- Overall accuracy on the test set
- Class-wise accuracy (female eyes vs male eyes)

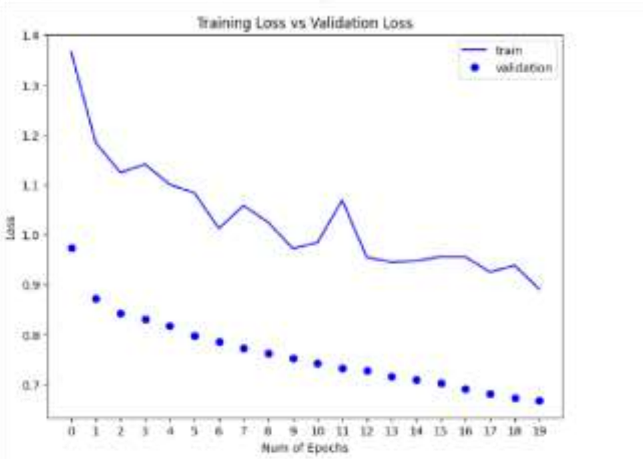


International Journal of Academic Information Systems Research (IJAISR)
ISSN: 2643-9026
Vol. 10 Issue 2 February - 2026, Pages: 35-41

5.2 Test Results

- Overall Test Accuracy:





Class-wise performance:

- Overall Test Accuracy: 65.67% (396/603).
- Accuracy on female eyes: 67.16% (180/268) • Accuracy on malee yes: 64.48% (216/335).

VI. DISCUSSION

The experimental results demonstrate that a transfer learning strategy based on the VGG16 architecture is well suited for the task of binary eye-image classification. By leveraging pretrained convolutional filters learned from large-scale natural image datasets, the model is able to extract meaningful visual representations from eye images despite limited domain-specific training data. The observed performance confirms that low-level and mid-level features such as edges, contours, and texture patterns learned during pretraining remain highly transferable to biometric image analysis tasks.

Freezing the pretrained backbone during the initial training phase plays a critical role in stabilizing the optimization process and reducing the risk of overfitting. Since the dataset used in this study is relatively constrained in size compared to large-scale vision benchmarks, updating all network weights from the outset could lead to memorization of training samples rather than generalizable feature learning. By restricting training to the newly added classification layers, the model benefits from the robustness of pretrained representations while adapting only the final decision boundaries to the specific binary classification task. This strategy also accelerates convergence and lowers computational cost, making it suitable for reproducible experimentation in cloud-based environments such as Google Colab.

Data augmentation further contributes to improved generalization performance by simulating realistic variations commonly encountered in eye-image acquisition. Random transformations such as rotations, translations, zooming, and horizontal flipping encourage the network to learn invariant features that are less sensitive to small changes in orientation and position. As a result, the trained model becomes more resilient to moderate pose differences and illumination variability, which are typical sources of noise in real-world biometric datasets. This confirms the importance of augmentation as a regularization mechanism when working with visually similar classes and limited training samples.

Despite these strengths, certain misclassification cases can still be attributed to challenging visual conditions. Image blur and low illumination significantly reduce the visibility of fine-grained texture cues around the iris and sclera regions, which are essential for distinguishing subtle anatomical differences. Occlusions caused by eyelashes and eyelids further obscure discriminative regions, limiting the amount of usable information available to the network. In addition, reflections from lighting sources and background artifacts introduce spurious patterns that may be incorrectly interpreted as class-relevant features. These factors collectively degrade the reliability of extracted feature representations and increase the likelihood of prediction errors.

Another potential limitation arises from dataset composition. If one class (male or female eyes) is overrepresented, the learned decision boundary may become biased toward the dominant class, resulting in inflated accuracy but reduced sensitivity to the minority class. Such imbalance can compromise the clinical or biometric reliability of the system, particularly in applications requiring fair and unbiased classification. Addressing this issue is therefore essential for ensuring robust and equitable performance.

Future work may focus on several avenues to enhance model effectiveness. First, after initial convergence with a frozen backbone, selectively fine-tuning the upper convolutional layers of the pretrained network could allow the model to learn more domain-specific features while preserving the stability of lower-level representations. Second, stronger or more diverse augmentation strategies—such as contrast adjustment, brightness variation, and slight elastic deformations—could further improve robustness to illumination changes and sensor noise. Third, incorporating class-weighted loss functions or resampling strategies would help mitigate the effects of class imbalance and promote fairer classification outcomes. Finally, replacing the VGG16 backbone with more recent and parameter-efficient architectures, such as ResNet or EfficientNet, may yield improved accuracy and faster convergence due to their enhanced representational capacity and optimized design.

Overall, the findings validate the effectiveness of transfer learning for eye-image gender classification and highlight the importance of preprocessing, augmentation, and architectural choices in achieving reliable performance. The proposed framework provides a strong baseline for future research and can be extended to more complex biometric or medical image classification tasks with appropriate architectural and data-centric refinements.

VII. CONCLUSION

This paper presented a complete deep learning pipeline for binary eye-based gender classification using an Eye Dataset and a transfer learning framework built upon the VGG16 architecture. The proposed approach integrates standardized image preprocessing, data augmentation, model checkpointing, and systematic test-time evaluation into a unified and reproducible workflow. By leveraging pretrained convolutional features, the model is able to learn discriminative visual patterns from eye images while reducing training complexity and mitigating overfitting.

Experimental results demonstrate that the proposed system achieves an overall test accuracy of 65.67%, with class-wise performance reported separately for both female and male eye categories. These findings indicate that transfer learning with VGG16 can provide a meaningful baseline for eye-based gender classification, despite the inherent challenges posed by image quality variations and subtle inter-class visual differences.

The developed pipeline establishes a solid foundation for future research in this domain. Potential extensions include fine-tuning higher layers of the pretrained backbone to capture more task-specific features, incorporating stronger and more diverse augmentation strategies, and adopting additional evaluation metrics such as precision, recall, and F1-score to obtain a more comprehensive assessment of model performance. Collectively, these improvements could enhance robustness and reliability, particularly in real-world biometric and vision-based classification scenarios.

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