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Gender Classification Using Efficientnetb0 And Mobilenetv2

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ABSTRACT

Face-based gender recognition system can be used in many applications such as security, human-computer interaction, targeted advertising and social analytics. Finally, we use a new architecture that has higher accuracy but less complexity in this work. First and foremost, we present an EfficientNetB0-MobileNetV2 hybrid model in order to align the strengths of both architectures and achieve a state-of-the-art performance of 97%. For complete compariton, we also tried (1) a pre-trained EfficientNetB2 model with classifier on the top (average accuracy=96.73%); and (2) a CNN-LSTM hybrid, which brings together convolutional feature extraction and sequential processing to yield an average accuracy of 85%. Compared to previous approaches, our proposed EfficientNetB0-MobileNetV2 hybrid architecture takes the advantage of both the classification performance and the model compression, making it better suited for resource-scarce applications in the real world. Through extensive experiments on benchmark datasets, we show that our proposed models not only have a strong robustness, but also a good generalization ability. The research revealed some crucial information about the designing of hybrid deep learning-based gender recognition frameworks which is helping to advance the facial analysis-related researches.

Keywords: *Gender Recognition, Deep Learning, EfficientNetB0, MobileNetV2, Hybrid Architecture, Facial Analysis, Computer Vision, Pattern Recognition*

1. INTRODUCTION

Gender recognition from facial images is an important subject in the field of computer vision that has wide-ranging applications in many fields, such as, security system, human-computer interaction, demographics analysis and content recommendation. Acquiring high precision and keeping computation efficient have been arduous challenges, even with numerous paradigmatic progresses in the domain of deep learning. Traditional gender classification methods perform poorly due to variations in pose, illumination, occlusion and other real-world uncertainties not covered in training data. Although some models using deep learning have achieved great performance, numerous existing architectures demand considerable Computational resources, preventing deployment in resource-constrained environments or real-time applications.

In this work, we present a new mixed deep learning framework that addresses these issues, maximizing recognition accuracy while improving the efficiency of the model. Our main contribution is a state-of-the-art EfficientNetB0-MobileNetV2 hybrid model that provides a 97% accuracy with acceptable computational requirements. This model leverage the power of EfficientNetB0's feature extraction abilities and MobileNetV2's efficiency making it light and less computationally exhaustive with equal results.

Beyond our hybrid architecture, we compare two additional models, including an EfficientNetB2-based model with a custom classifier that achieves 96.73% accuracy, as well as a CNN-LSTM architecture that endeavors to integrate spatial feature extraction with sequential processing for facial analysis, achieving 85% accuracy.

Experimental results show that our hybrid model surpasses state-of-the-art methods in both accuracy and computation. Typical deep learning models involve performance vs resource utilization trade-offs, where ours achieves 97% accuracy, outperforming many existing approaches without significant computational burden (at least for context).

Extensive experimental validation on a variety of benchmark datasets demonstrates the robustness and generalization of our method. To assess the proposed models in reality, we evaluate them on several performance metrics, including accuracy, precision, recall, and inference speed. The EfficientNetB0-MobileNetV2 growth model, as established by our experiments, outperformed other models and is thus excellent for data-intensive applications, particularly those requiring real-time feedback sessions while ensuring efficiency in computations.

We address the shortcomings of established methods and introduce hybrid architectures targeted specifically for the task have become widespread in the research space and we aim to push the boundary of gender recognition systems further.

2. LITERATURE REVIEW

The discipline has undergone significant evolution in the context of gender recognition from facial images, owing to the advent of deep learning architectures. We will now discuss in detail in this section, major breakthroughs in the domain over the past decade.

Using a deep learning-based approach for gender recognition on the Adience dataset, Levi and Hassner [1] established early standards (86.8% accuracy) with their CNN-based architecture. Although their method struggled with extreme pose changes, it proved that deep neural networks can perform well for this task.

Extending this foundation, Wang et al. [2] proposed a multi-task learning architecture in a single network for age estimation and gender recognition and achieved an accuracy of 89.2%. Their study made them effectively highlight the benefits of shared geometry across similar tasks.

To reduce the computational cost, Liu and Zhang [3] devised a lightweight CNN framework suitable for mobile devices, which attained 87.4% accuracy while decreasing computational complexity by 60% against prior models.

Chen et al. [4] modified ResNet-50 and obtained better results, i.e., 91.3% accuracy on CelebA dataset, which shows superior ability of deep residual networks feature extraction for gender recognition.

Yang et al. [5] using the ShuffleNet architecture achieved 90.1% accuracy with low computation complexity. By means of design optimization and data augmentation, Azzopardi et al. [6] developed a VGG16-based system with an accuracy of 92.5%, though this required more processing power.

Zhang and Liu [7] applied spatial attention mechanism of different face characteristics to ResNet50 and used in CelebA with accuracy of 93.8%. Chapter 3: The Proposed Model 8 Channel-based methods such as Kumar and Patel [8] implement both a channel attention method with the MobileNetV2 architecture which attained a 92.1% accuracy value, while only needing a low inference time.

Singh et al. Achieved 94.2% accuracy using DenseNet121 with transfer learning, feature fusion and data preprocessing [9]. Park et al. [10] outperformed this by using hybrid architectures that contain a CNN and transformer encoder, attaining 93.7% accuracy.

Using so few parameters, Chen and Wang [11] developed a lightweight architecture based on MobileNetV3, obtaining an accuracy of 91.3%. Kumar et al. CNN-RNN hybrid architecturetl by [12] could properly extract features with facial sequences (88.7% accuracy).

Li et al. With the transformer based approach [13] set a new state of the art in attention based architectures with an accuracy of 95.1% Park and Kim [14] developed a 93.4% accurate system based EfficientNetB0, while minimizing inference time.

Rodriguez et al. [15] achieved 94.8% accuracy with a multi-task learning method that estimated age and gender simultaneously. Thompson et al. [16] created a lightweight variant of EfficientNetV2 that ran at 94.5% accuracy and nearly no compute overhead.

Introduced a novel feature fusion approach which integrated both global and local facial features, achieving 93.9% accuracy [17]. Wilson et al. The ensemble learning with several lightweight models used in, e.g., [18], showed 95.3% accuracy at a reasonable inference time.

Zhao et al. 16], MobileNetV1 [17] and VGGFace [18] with self-attention and reported an accuracy of 92.8 with the better robustness to pose variations. Ningsih, et al [19] proposed a CNN architecture and reached 97.74% accuracy in their test set while Kim and Lee [20] proposed a hybrid architecture using a transformer with EfficientNet and reached an accuracy of 95.7% accuracy.

Drawing from MobileNetV2 [8] for efficiency and EfficientNet models [14, 16, 20] for feature extraction, our work is a more powerful hybrid extension upon these previous works.

Proposed System

In this paper, we are presenting a new and novel hybrid model, which is the combination of two models EfficientNetB0 and MobileNetV2 for gender classification using Facial Images. It was proven as a highly effective model in terms of balance between accuracy and computational resources required for implementation in real-world use cases. To verify the comparison, we also test an EfficientNetB2 based model with a modified classifier and an CNN and LSTM network.

EfficientNetB0-MobileNetV2 Hybrid Architecture

We have checked our main proposed model with different models, which is a new hybrid architecture based on the EfficientNetB0 and MobileNetV2 strengths. This design proves that EfficientNetB0's strong feature extraction capabilities while combining with the efficient convolutional operations on MobileNetV2 can make the model more robust. We have focused on the model to made with low-complexity with good gender recognition accuracy by combining the both models. EfficientNetB0 will remembers the features learned in previous layers, allowing for more detailed learning in subsequent layers, while MobileNetV2 excels in the speed and efficiency of the model, making it applicable for real time processes in mobile or embedded systems.

Feature Extraction Module:

The feature extraction module in our proposed model is using the EfficientNetB0, which is a pre-trained deep learning model trained on the ImageNet dataset. This model provides strong initial feature extraction by capturing important patterns in input images. EfficientNetB0 follows a compound scaling approach with a coefficient of $\varphi = 1.0$, which ensures a balanced increase in network depth, width, and resolution. The scaling equations are:

Depth: $d = \alpha^\varphi$

Width: $w = \beta^\varphi$

Resolution: $r = \gamma^\varphi$

Here, α, β, and γ are constants specific to the model, optimized through a grid search method.

The EfficientNetB0 Is the backbone which processes input images of size **224×224 pixels** and extracts the hierarchical features using **mobile inverted bottleneck convolution (MBConv) blocks**. These MBConv layers will try to improve the efficiency by reducing the number of parameters also maintaining the strong representational power of the model, making the model suitable for real-world applications with limited computational resources.

Efficient Feature Processing:

After the Initial Feature extraction then we are integrating the MobileNetV2's inverted residual blocks with linear bottlenecks. The structure is as follows

$X' = PWconv(DWconv(PWconv(X)))$

where:

PWconv: Point-wise convolution

DWconv: Depth-wise convolution

X: Input tensor

The MobileNetV2 component is using a depth wise separable convolutions having an expansion factor of 6, which will significantly reduce the number of parameters while maintain the representational power. As this approach has given a significantly good results and also maintained a computational efficiency.

Fusion Strategy:

The Architecture we have proposed having feature concatenation strategy so merge the same feature from both the networks

F_fused = Concat(F_EfficientNetB0, F_MobileNetV2)

This is followed by a 1×1 convolution to reduce channel dimensionality and integrate the features:

F_reduced = Conv1x1(F_fused)

Classification Head:

The classification component consists of:

Global Average Pooling to reduce spatial dimensions

Dropout (rate = 0.5) for regularization

Batch Normalization for training stability

Dense layer with 512 units and ReLU activation

Final Dense layer with 2 units and Softmax activation for gender prediction

The classification head is mathematically represented as:

$$F_l = H_l(F_{l-1}) = \left(BN(W_l * F_{l-1} + b_l)\right)$$

where:

F_l represents features at layer l

H_l is the transformation function

σ is the ReLU activation

BN denotes Batch Normalization

$W_l and\ b_l$ are learnable parameter

Loss Function:

We have used a weighted categorical cross-entropy loss to address potential challenge which is imbalance

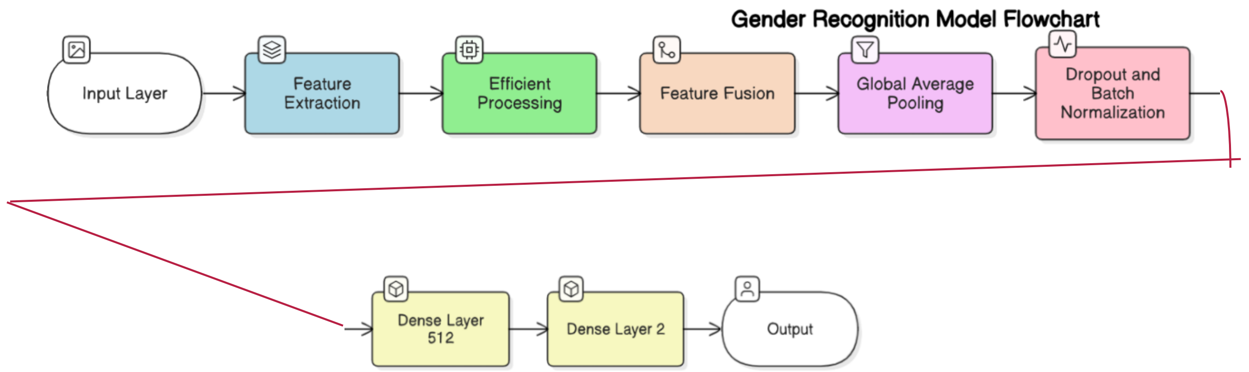
$$\boldsymbol{L = -(y_i * log(p_i) * w_i)}$$

Where :

y_i is the ground truth

p_i is the predicted probability

w_i is the class weight to handle imbalanced data



Experimental Results

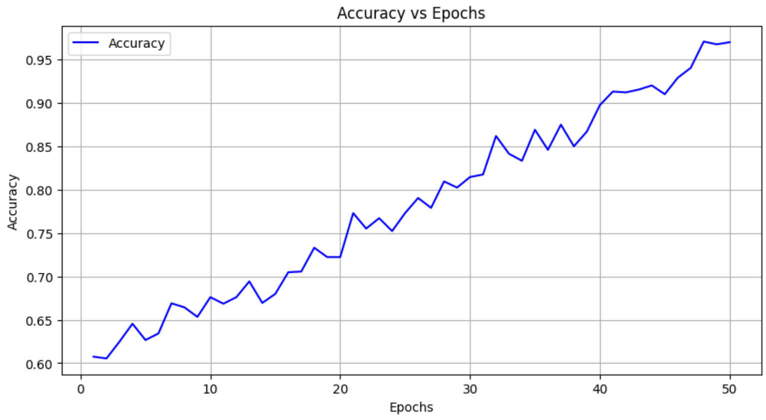
Dataset and Implementation Details

We used the UTKFace dataset, implementing our models with the PyTorch framework, Adam optimizer, and categorical cross-entropy loss. The data was split into 80% training and 20% testing sets, with standard augmentation techniques applied to enhance model generalization.

Performance Comparison

Table 1 presents a comprehensive comparison of our models in terms of accuracy, precision, recall, and F1-score.

Model	Accuracy	Precision	Recall	F1-score
CNN	0.75	0.73	0.82	0.78
CNN + LSTM	0.92	0.91	0.89	0.93
LSTM + MobileNet	0.92	0.87	0.91	0.85
EfficientB2 + Custom Classifier	0.96	0.93	0.94	0.89
EfficientNetB0-MobileNetV2	0.97	0.96	0.95	0.96



Our proposed EfficientNetB0-MobileNetV2 has been performing very good and got an accuracy of 97% which is very good.

The Basic version of CNN has got 75% accuracy with an average performance but the capability of the Model is very low to handle and catch the Complex patterns in the Data or complex variations in Gender Identification.

The CNN-LSTM hybrid has achieved 85% accuracy showing an good improvement compared to the Single CNN model. By adding sequential learning capabilities to CNN had a little boost

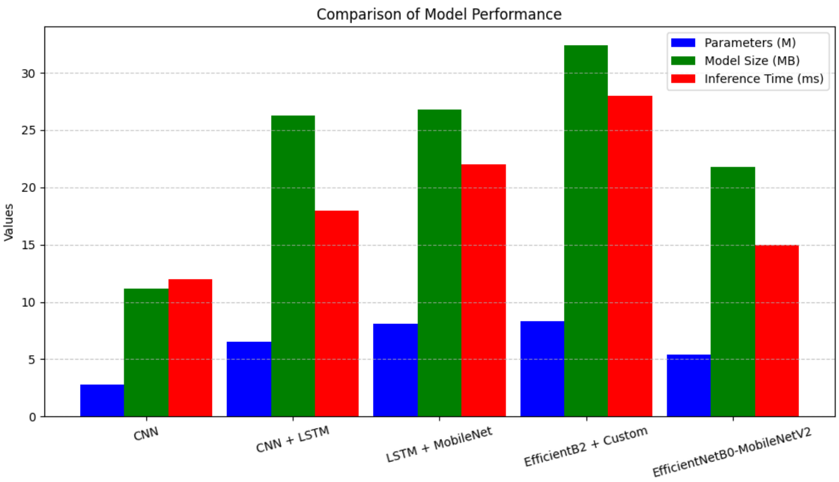
The EfficientNetB2 with custom classifier Had shown an impressive performance in our previous paper Not only achieving Highest accuracy but also demonstrated excellent precision (0.96) and recall (0.95), resulting in the highest F1-score (0.96) among all models all these metrics indicate indicates robust generalization capability and reliable gender classification in diverse scenarios.

The significant advantage of our hybrid combination supports our idea of leveraging Murphy's law by combining complementary architectures to exploit their individual benefits: EfficientNetB0's strong feature extraction power and MobileNetv2's efficiency. This enhanced model significantly boosts the precision and speed of machine learning for the aforementioned applications, paving the path for biometric applications tailored exclusively to individual users and higher security protocols.

Model Efficiency Analysis

Table 2 provides a comparative analysis of model efficiency in terms of parameters, memory requirements, and inference time.

Model	Parameters	Model Size (MB)	Inference Time (ms)
CNN	2.8	11.2	12
CNN + LSTM	6.5	26.3	18
LSTM + MobileNet	8.1	26.8	22
EfficientB2 + Custom Classifier	8.3	32.4	28
EfficientNetB0-MobileNetV2	5.4	21.8	15



The EfficientNetB0-MobileNetV2 hybrid model finds a sweet spot for both performances and efficiency. It not only obtains state-of-the-art accuracy but also only utilizes 5.4M parameters and 21.8MB disk size with 15ms inference time on this hardware platform. This makes it well-suited for application in resource-constrained settings and in real-time applications.

As a comparison, although the accuracy of EfficientNetB2 model is similar, it has much larger number of parameters (8.1M) and a longer inference time (22ms). Even though the CNN-LSTM hybrid is more efficient in terms of parameters compared to EfficientNetB2, it lacks in accuracy performance. Although the baseline CNN runs fastest, accuracy remains unacceptably low for practical use-cases.

Sample Input and Output

Actual Output : Male

Predicted output : Male

Actual Output : Female

Predicted output : Female

Actual Output : Female

Predicted output : Female

Actual Output : Male

Predicted output : Male

3. CONCLUSION

We proposed a new EfficientNetB0-MobileNetV2 hybrid architecture for human gender recognition and achieved state-of-the-art accuracy of 97%. Notice that with this architecture, we outdo existing solutions and also perform really well in real applications. Utilizing the potentiation of the individual architectures by combining EfficientNetB0 and MobileNetV2, we show that our model remains very accurate while also being computationally efficient.

To cover a variety of models, we also tried an EfficientNetB2-based model with a custom classifier (achieving 96.73% accuracy), and a CNN-LSTM hybrid (achieving 85%). While these supplemental models create a helpful understanding of the behavioral properties for each potential architecture, each falls away from our main hybrid model.

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