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FACIAL IMAGE BASED GENDER CLASSIFICATION SYSTEM USING DEEP LEARNING MODEL

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Abstract - *This paper proposes a real-time gender classification system leveraging deep learning and webcam input. Convolutional Neural Network (CNN) architecture is designed to extract hierarchical features from facial images. Training involves data preprocessing, model optimization, and validation. Integration with webcam feed is achieved using Open CV, allowing the real-time image acquisition and classification. Deployment involves web application development for seamless user interaction. Testing demonstrates robustness and accuracy, with evaluation metrics indicating reliable performance. Overall, the system offers a practical solution for real-time gender classification from facial images. The CNN architecture is crucial for extracting meaningful features from facial images. It typically consists of multiple convolutional and pooling layers followed by fully connected layers for classification. Data preprocessing steps may include normalization, resizing, and augmentation to enhance the model's ability to generalize. Model optimization techniques such as learning rate, scheduling and regularization help to improve the performance and prevent over fitting. Integration with OpenCV enables the system to capture live video streams from a webcam, process the frames, and perform gender classification in real time. This integration allows seamless interaction with the system, making it suitable for applications like video conferencing, surveillance, and human-computer interaction. Overall, this work demonstrates the feasibility and effectiveness of deep learning for real-time gender classification.*

Key Words: *Gender classification, Convolutional Neural Network, open CV, Deep learning, Transfer Learning.*

1.INTRODUCTION

Gender classification from facial images is a crucial task in computer vision with numerous applications such as security, marketing, and human-computer interaction. The goal is to automatically determine the gender of a person from an image and open CV. This study presents a facial image-based gender classification system that utilizes a deep learning model for efficient and accurate gender prediction. Deep learning models, such as convolutional neural networks (CNNs), are particularly well-suited for this task because they can automatically learn complex patterns and features from raw image data. These models can be trained on large datasets of labeled facial images to effectively distinguish between male and female faces. The proposed system leverages convolutional neural networks (CNNs) to automatically learn discriminative features from facial images, eliminating the need for manual feature extraction. The system's architecture consists of multiple convolutional layers followed by fully connected layers for gender classification. Data preprocessing techniques such as normalization and augmentation are applied to enhance the model's generalization ability.

Face images contain valuable information for biometric recognition. Gender, age, and race can be extracted from faces, raising privacy concerns. GDPR regulates data usage, limiting information extraction without consent. Previous work used SAN to confound gender extraction from faces. We propose a gender detection system based on VGG19 for facial images, ensuring privacy. Our system integrates with OpenCV for real-time gender classification from webcam images. Experiments show improved gender detection while preserving face matching utility. This system addresses privacy concerns in biometric applications.

Gender recognition from faces, a key human ability, is gaining interest for machine applications. It's used in social robotics and digital signage for personalized interactions and targeted advertising. Real-world applications require in reliable performance under challenging conditions, such as varying lighting and poses. Running gender recognition on embedded devices, like robots or cameras, is challenging due to limited resources. This paper proposes a deep learning architecture, based on Mobile Net v2, optimized for gender recognition. The network is designed to balance accuracy and speed, making it suitable for real-time applications on embedded devices with limited resources.

Crucial biometric task with applications in various fields, often studied using different modalities. Facial modality, being universal and acceptable, is widely used. Deep learning has greatly improved gender classification, surpassing traditional methods. However, the need for large training datasets raises privacy concerns when using real images. To address this, we investigate the use of fake data generated by GANs for training, focusing on privacy and data augmentation. This paper presents a new approach using Deep fake faces for training CNNs, evaluated on real datasets. Additionally, we offer a substantial dataset of over 200,000 deep fake faces to facilitate further research in this domain. The deep learning model is trained on a large dataset of labeled facial images to learn gender-specific features. Integration with Open CV enables the system to capture real-time facial images from a webcam and classify the gender of the person in the image. The system achieves high accuracy in gender classification, making it suitable for real-world applications requiring fast and reliable gender prediction from facial images. Experimental results demonstrate the effectiveness of the proposed system in achieving accurate gender classification in real-time scenarios.

2. RELATED WORKS

Gender classification from human faces has been a topic of extensive research, with various approaches proposed in the literature. Typically, gender classification involves preprocessing, feature extraction, and classification phases. Investigated gender detection in images using VGG19 model is known for its image classification accuracy. Prior methods struggled with generalization to new data and classifiers. Our approach seeks to enhance VGG19's gender detection by improving generalization and robustness to unseen classifiers.

In [1], Arun Ross et al. utilized on preserving soft-biometric privacy in face images. Methods like SAN and SensitiveNet aim to confound gender classifiers while retaining face matching performance. These methods, however, may struggle to generalize to unseen classifiers. To address this issue, FlowSAN was proposed to successively reduce the performance errors of unseen gender classifiers. The goal is to improve generalizability and practicality in real-world applications. Further, it was noted that the performance of augmentation technique M-COTS on CelebA dataset images was only 85.6%.

Antonio Greco et al [2] demonstrated a method which locates faces in images using model-based approaches. Normalization and alignment adjust the face to a standard position, usually based on facial landmarks. Feature extraction and classification use these normalized faces to determine gender, often using handcrafted or trainable features, such as color, shape, and texture, with methods like SVMs or deep convolutional neural networks. Recent advancements aim to combine these steps for more efficient and accurate gender recognition and it was found that even with few feature maps and a reduced layer hierarchy, there is no significant performance drop below 97.70%.

Avishek Garain et al [3] proposed a technique in which human faces involves preprocessing, LBP feature extraction, and classification with SVM and other classifiers. Recent studies focus on CNNs for their effectiveness. GANs are used for image generation, creating synthetic data through a generator and distinguishing between fake and real data with a discriminator. GAN-generated faces have been used for data augmentation and improving face recognition in challenging conditions. Researchers have also used GANs for anti-spoofing scenarios and preserving human gender in generated faces. The VGG16 allows an AUC score of 86.7%.

The recognition from 3D human shapes is less explored compared to 2D image-based methods. Previous works used geodesic distances and hand-crafted features but were limited by posture variation and small datasets. Our approach is posture invariant, requires no landmarks, and is trained on a large dataset. We propose a new descriptor using biharmonic distances for gender classification. Geometric deep learning, especially CNNs, has shown promise for 3D shape analysis, but acquiring 3D data is challenging. Our method uses a deep neural network with biharmonic distance-based features for gender recognition of 3D human shapes, addressing these challenges. The dataset is randomly split into a 70% train set and a 30% test set. The testing accuracy of the proposed method (PDD+DNN) is 96.7%, which is much better than the PDD+SVM with an accuracy of 73.5% [4].

Gender classification research has advanced significantly, particularly in human-face analysis using methods like SVM, LBP, and CNNs. However, these approaches often rely on small datasets and may overlook privacy concerns. On the other hand, generative adversarial networks (GANs) have emerged as powerful tools for creating synthetic faces, including deep fake faces, which are highly realistic but represent non-existing identities. GANs have also been used to augment face recognition systems, improving their performance. Efforts have been made to detect fake images to prevent misuse. While GANs offer exciting possibilities, ethical considerations around privacy and security are crucial. The best performances were returned with the fake trained VGG16-based classifiers [5].

A self-joint attention mechanism is used for gender classification using RGB-D camera data, addressing challenges like varying views, poses, and scales. Our method leverages attention to combine features from both modalities, capturing their inter-dependencies for enhanced discriminative learning. Through a comprehensive ablation study, we fine-tune our system parameters, achieving superior performance over the state-of-the-art. On a public RGB-D gender dataset, our method outperforms existing approaches by significant margins of 4.7%, 7.5%, and 8.7% across three distinct testing sets. The results show that the accuracies of most of the subsets are the same around 91.88% [6].

JSE features are used for skeleton-based gender classification. This method involves three steps: (1) creating a human body-centered skeleton representation, (2) extracting JSE features, and (3) classification. It computes the transverse, frontal, and median planes from the input gait sequence for skeleton representation, then extract JSE features for these planes. These features are concatenated into a feature vector and used to train a classification model. This method achieved state-of-the-art performance in accuracy and other metrics across four publicly available gait datasets. Future work includes testing the method on partially occluded body parts and making it robust to such scenarios. JSE-SVM technique also achieves a good Fβ score of 85.7% or above. Compared to the existing techniques, F1-KNN achieves the highest Fβ score of 86% [7].

An approach using DNN architecture with synthetic data generation and continuous wavelet transform (CWT) is proposed in [8]. The system consists of three main modules: data generation, feature extraction, and gender detection. Synthetic data are first generated to expand the training dataset, followed by the application of CWT to extract 2D feature matrices from the sensor data. For classification, a hybrid DNN architecture combining CNN and LSTM layers is employed. The proposed method achieves high detection rates, surpassing previous approaches on various public datasets. Additionally, the model has potential applications in activity recognition, age group estimation, and user identification using smart device sensor data. Future work will focus on real-time deployment of the model on smart devices. The steps such as generating synthetic data, applying CWT, and using 3-Layer CNN + LSTM model significantly improve the classification accuracy as 88.1%. The proposed method for high-resolution facial image age and gender classification employs the Residual of Residual Network (RoR) architecture. It incorporates two effective techniques to enhance performance: pre-training based on gender and utilization of a weighted loss layer during training for age estimation. These mechanisms contribute to improving the accuracy of age estimation in the model's classification tasks. Pre-training on ImageNet is used to alleviate over fitting. By RoR or Pre-RoR with two mechanisms, the authors obtain new state-of-the-art performance on the Adience dataset for age group and gender classification in the wild. Through empirical research, this study not only notably improves the accuracy of age group and gender classification but also investigates the utilization of RoR (Region of Interest) in processing large-scale and high-resolution image classifications in the future. So RoR-152+IMDB-WIKI are used to repeat the experiments. A new state-of-the-art performance with a single-model accuracy of 67.34±3.56% is achieved [9].

The CNN model was developed using the Keras library on the TensorFlow-based Deep Learning framework. A comparison was made among three CNN models pre trained on the ImageNet database: VGG-16, ResNet-50, and MobileNet. The training database was manually collected using Google Images and consists of 500 male and female samples, respectively. All models were trained with 100 epochs and a batch size of 16 using GPU-based hardware. The VGG-16 model delivered the best accuracy on the training set, followed by ResNet-50 and MobileNet. As a part of future work, other types of CNN models can be used for further investigation, such as InceptionResNetV2, InceptionV3, AlexNet, and DenseNet. VGG-16 yielded the best accuracy of 88.9% on the training set, followed by ResNet-50 achieving 87.9% and then MobileNet with 49%. [10].

3. METHODOLOGY

3.1 Dataset

Gender classification from face images is a common task in computer vision, often used in various applications such as security systems, demographic analysis, and personalized user experiences. The dataset should contain a large number of images labeled with the gender of the individuals depicted in the images. To train a gender classification model, a dataset with a large number of images of males and females is required. Some of the key considerations for creating or selecting a dataset for these tasks are Image Quality, Divercity, Balanced Classes, Labeled Data, Data Augmentation, privacy and ethics. Custom datasets can be created by collecting and labeling images from sources such as social media, online databases, or through crowdsourcing platforms. For the specified requirements of 23,000 female and 23,000 male images for training, and 5,800 female and 5,600 male images for testing, the dataset needs to be carefully curated and split into training and testing sets. Random selection should be used to ensure the dataset's randomness and avoid bias. Additionally, data augmentation techniques can be applied to increase the dataset's size and improve the model's performance.

3.2 Gender Identification

The proposed methodology for gender identification involves leveraging the VGG19 deep learning model with transfer learning. Transfer learning allows the model to use knowledge gained from training on one task to improve learning on a related task. By utilizing a pre-trained VGG19 model as a base and fine-tuning it on a facial dataset, the model can extract high-level features from facial images and learn to classify gender effectively. This approach is expected to enhance the model's performance and reduce the need for extensive training data.

3.3 Data Augmentation

Data augmentation is a technique used to artificially expand the size of a dataset by creating modified versions of images in the dataset. It involves applying various transformations to the original images to create new, slightly modified versions of the data. This helps in improving the model's performance and generalization. During the coding phase, we use *ImageDataGenerator* class from Keras to perform data augmentation. The Rotation Range, width_shift_range, height_shift_range, shear_range, zoom_range, horizontal_flip, Color jittering and Random Erasing parameters specify the range and types of transformations to apply to the images. Pre-processing is the transformation of raw data into a format suitable for the model. For image data, this often involves resizing the images to a standard size (e.g., 224x224 pixels for VGG19) and normalizing the pixel values to be in the given an range [0, 1].

3.3.1 Rotation

Rotating the image by a certain angle (e.g., 90 degrees) to introduce variations in the orientation of faces.

3.3.2 Shearing

Applying a shearing transformation to the image to change the shape of the face slightly.

3.3.3 Image Zoom

Zooming in or out of the image to simulate different distances from the camera.

3.3.4 Image Height Range

Adjusting the height of the image to simulate different head sizes.

3.3.5 Image Width Range

Adjusting the width of the image to simulate different face widths.

3.3.6 Image Horizontal Flip

Flipping the image horizontally to create a mirror image of the face.

3.3.7 Image Vertical Flip

Flipping the image vertically to create an upside-down version of the face.

3.3.8 Color Jittering

Adding random variations in brightness, contrast, and saturation to the image to simulate different lighting conditions.

3.3.9.Random Erasing

Randomly erasing parts of the image to simulate occlusions or missing data.

Table 1: Parameter setting for data augmentation:

Method	Setting
Rotation	40°
shearing	0.2
Image zoom	0.2
Image height range	0.2
Image width range	0.2
Image Horizontal	True
Image Vertical	True
Fill mode	'nearest'

3.4 Pre-processing

The preprocessing input function from tensorflow. The dataset is loaded using the flow from directory method of the Image Data Generator class. To preparing the input data in a way that is vgg19 for training a deep learning model. Preprocessing steps for this task are Image Resizing, Normalization, Face, Detection and Alignment, Data Augmentation, Label Encoding, Splitting the Dataset and Batching and Shuffling. These preprocessing steps are essential for preparing the input data for training a deep learning model for gender classification from facial images and input images are in the correct format and range expected by the VGG19 model. This method generates batches of augmented images from the specified directory, with each subdirectory representing a different class (e.g., male and female). The class_mode='binary' parameter indicates that we are performing binary classification. Implementing these steps will help ensure that the model performs optimally and produces accurate results.

3.4.1 Image Resizing

Resizing the images to a fixed size to ensure that all images have the same dimensions, which is required by most deep learning models.

3.4.2 Normalization

Normalizing the pixel values of the images to a common scale to facilitate faster convergence during training.

3.4.3 Face Detection and Alignment

Detecting and aligning faces within the images to ensure that the model focuses on the facial features relevant to gender classification. Techniques like MTCNN (Multi-Task Cascaded Convolutional Networks) can be used for this purpose.

3.4.4 Data Augmentation

As mentioned earlier, applying data augmentation techniques such as rotation, shearing, and flipping to increase the diversity of the training data and improve the model's generalization ability.

3.4.5 Label Encoding

Encoding the gender label as numerical values to facilitate training of the model.

3.4.6 Splitting the Dataset

Splitting the dataset into training, validation, and testing sets to evaluate the performance of the model on unseen data.

3.4.7 Batching and Shuffling

Batching the preprocessed images and shuffling the batches during training to introduce randomness and prevent the model from memorizing the order of the images.

3.5 Model Architecture

The VGG19 model is a deep convolutional neural network that has been pre-trained dataset. It consists of multiple convolutional and pooling layers, followed by a few fully connected layers at the end. In this architecture, we use the VGG19 model as a feature extractor. We remove the top (classification) layers of the VGG19 model because we want to retrain it for gender classification. On top of the VGG19 base model, we add a custom classifier for gender classification. We start by flattening the output of the last convolutional layer of the VGG19 base model. This converts the 3D tensor output into a 1D tensor that can be fed into a fully connected layer. Next we add a fully connected dense layer with 256 units and ReLU activation function. This layer helps in learning complex patterns in the flattened feature vector. Finally, we add another fully connected dense layer with a single unit and sigmoid activation function. This is the output layer that predicts the gender of the input image. The sigmoid activation function squashes the output value to a range between 0 and 1, representing the probability of the input image being male or female. We freeze the weights of the VGG19 base model to prevent them from being updated during training. Since the VGG19 model has already been trained on a large dataset. the features it has learned are likely to be useful for gender classification as well. Freezing the base layers allows us to leverage these features without modifying them. Printing the summary of the model provides information about the layers, their types, output shapes, and the no of trainable.

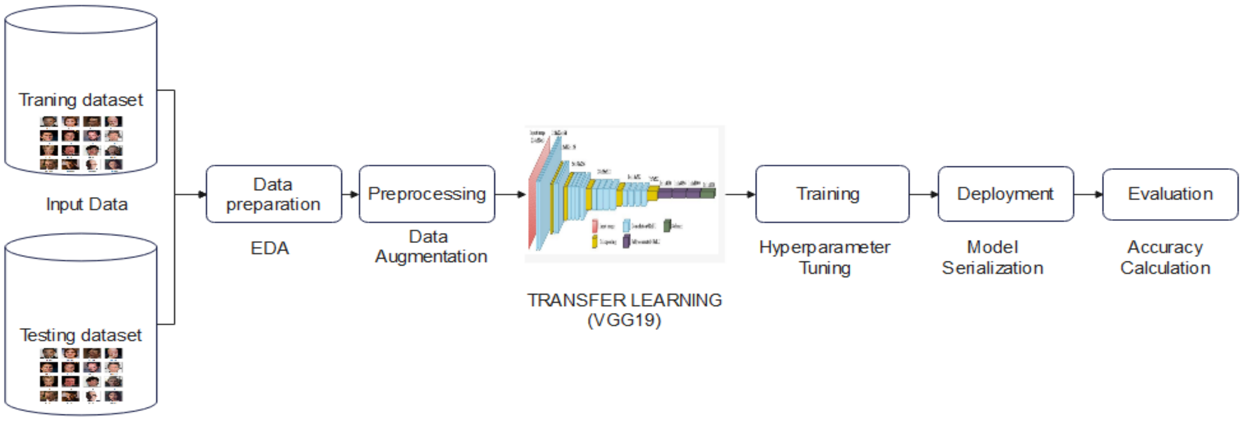

Fig 1: Block Diagram

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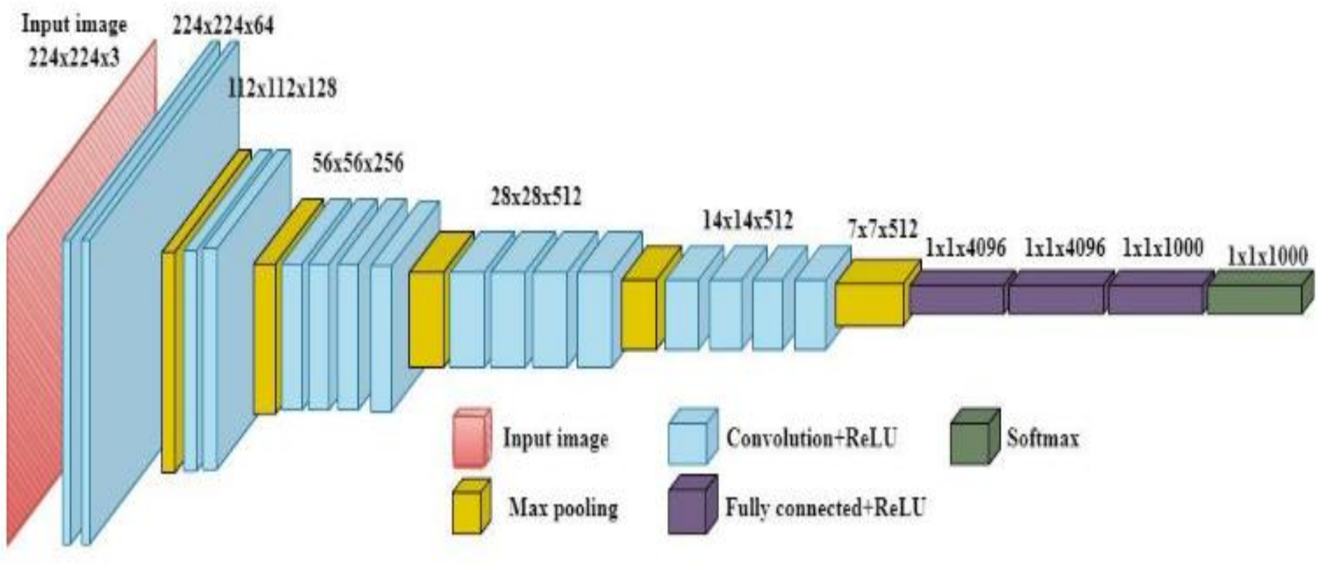

Fig 2: Architecture of VGG-19

3.6 Transfer Learning

Transfer learning with VGG19 involves leveraging a pre-trained VGG19 model, which has been trained on a large dataset and adapting it for a new task, such as gender detection. The pre-trained VGG19 model is loaded, which contains convolutional layers that have learned to extract features from a wide range of images.

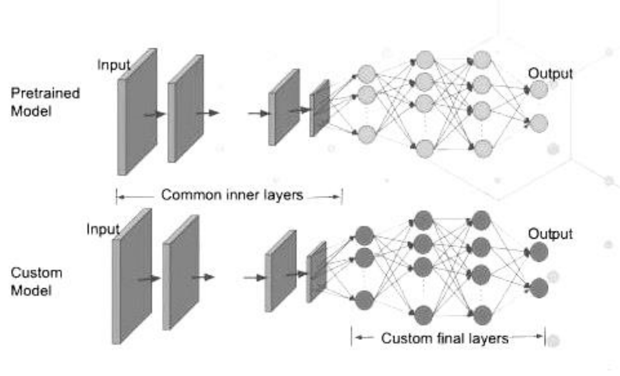

Fig 3: Transfer Learning Architecture

3.6.1 Customizing Model Architecture

The architecture of the VGG19 model is customized to suit the gender detection task. This typically involves removing the original classification layers and adding new layers for gender classification.

3.6.2 Freezing Pre-Trained Layers

The weights of the pre-trained layers in VGG19 are frozen to preserve the learned features. This ensures that these layers are not updated during training, retaining their valuable knowledge.

3.6.3 Training the Model

The customized VGG19 model is trained on a dataset of labeled images for gender detection. During training, the model learns to classify genders based on the features extracted from the images.

3.6.4 Train the images

We create variations of our training images (like rotating or flipping them) to make our model more robust. We use the augmented images to train our model. The model learns to associate features in the images with gender labels (male or female).

4. EXPERIMENTAL SETUP

4.1 Classification

Transfer learning (TL) with convolutional neural networks (CNNs) is employed to enhance performance in gender detection by leveraging knowledge acquired from similar tasks learned beforehand. This approach has significantly advanced gender detection applications, particularly in image analysis, by addressing challenges related to data scarcity and optimizing time and hardware utilization. However, in many studies, transfer learning for gender detection has often been configured without clear guidelines or standardized methodologies.

4.2 VGG19

The VGG19 model is a deep convolutional neural network architecture that was proposed by the Visual Geometry Group (VGG) at the University of Oxford. It is an extension of the original VGG16 architecture, with 19 layers (hence the name) compared to VGG16's 16 layers. VGG19 is known for its simplicity and uniform architecture, making it easy to understand and implement. The model consisting of 19 layers with weights, is a deep convolutional neural network widely used in image classification tasks, including gender detection. The architecture comprises 16 convolutional layers and 3 fully connected layers. When applied to gender detection, the input to the VGG19 model is typically a 224 × 224 size image with three color channels (RGB). Prior to feeding the image into the model, the average RGB value is subtracted to normalize the data and improve convergence during training. The convolutional layers in the VGG19 model employ a small receptive field size of 3 × 3 with 1 pixel padding and stride. This has been widely used as a base architecture for various computer vision tasks, including image classification, object detection, and image segmentation. It has also been used as a feature extractor for tasks such as transfer learning, VGG19 is a popular deep learning architecture known for its simplicity, effectiveness, and ease of implementation, making it a valuable tool for researchers and practitioners in the field of computer vision.

a) Layer Configuration

VGG19 consists of 16 convolutional layers, followed by 3 fully connected layers and a soft max output layer. The convolutional layers are grouped into blocks, with each block containing multiple convolutional layers followed by a max-pooling layer.

b) Filter Size

The convolutional layers in VGG19 use 3x3 filters with a stride of 1 and same padding, which helps preserve the spatial dimensions of the input.

c) Pooling

VGG19 uses max pooling with a 2x2 window and a stride of 2 after every two convolutional blocks to reduce the spatial dimensions of the feature maps.

d) Activation Function

The activation function used in VGG19 is the rectified linear unit (ReLU), which helps introduce non-linearity into the model.

e) Fully Connected Layers

The last three layers of VGG19 are fully connected layers, which are used to map the features extracted by the convolutional layers to the output classes.

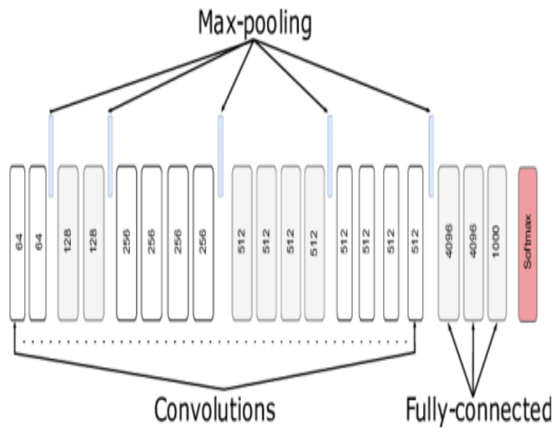

Fig 4: VGG-19 model architecture.

4.3 Hyper Parameters

The selection of parameter values for gender detection posed initial challenges, as the outcomes tended to fluctuate based on the chosen values. Consequently, we conducted numerous experiments, meticulously adjusting specific parameters until achieving optimal performance. The table below showcases the parameter values corresponding to the highest performance achieved.

Table 2: classification models key parameters

Data	Batch size	No of Epochs	Type of optimizer	Type of metrics
50000	32	100	Adam	Accuracy, F1 score

4.4 Performances Metrics

To assess the performance of models in gender detection, we utilized the confusion matrix as the primary evaluation metric. Specifically, the parameters are as follows: TP (True Positives) represents the number of images correctly classified as the correct gender, TN (True Negatives) represents the number of images correctly classified as the correct non-gender, FP (False Positives) represents the number of images incorrectly classified as the opposite gender, and FN (False Negatives) represents the number of images incorrectly classified as the opposite non-gender.

a) Accuracy:

Accuracy is a crucial metric that measures the overall correctness of a model's predictions. It is calculated using the formula

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

b) Precision:

Precision assesses the model's ability to correctly classify positive cases. It is calculated as

$$\text{Precision} = \frac{TP}{TP+FP}$$

***c)* Sensitivity (Recall):**

Sensitivity, also known as Recall, evaluates the model's ability to correctly classify all positive cases. It is calculated as

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

d) F1 Score:

F1 Score is a composite metric that balances accuracy and precision. It is calculated as the harmonic mean of precision and recall, providing a single measure of a model's performance.

$$\text{F1Score} = \frac{2TP}{2TP+FP+FN}$$

5. RESULT AND DISCUSSION

Table 3: Performance Metrics measurements

No. of classes	Precision	Recall	F1 Score	Accuracy
Male	90	100	95	95
Female	100	92	96	

Table 4: Existing vs proposed solution comparison table

Methodologies	Accuracy
DNN	90%
flowSAN	89%
MobileNet	92%
VGG19	95%

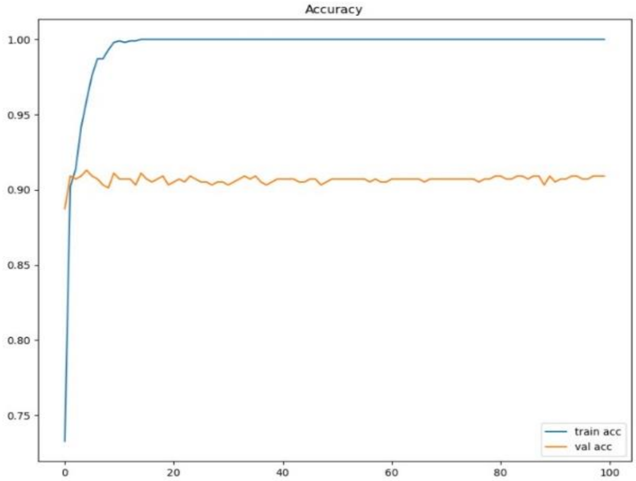

Fig 5: Accuracy evolution of the model (VGG19)

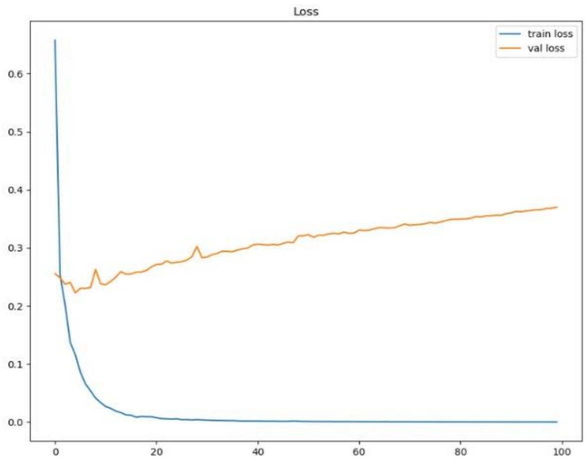

Fig 6: Loss evolution of the model (VGG19)

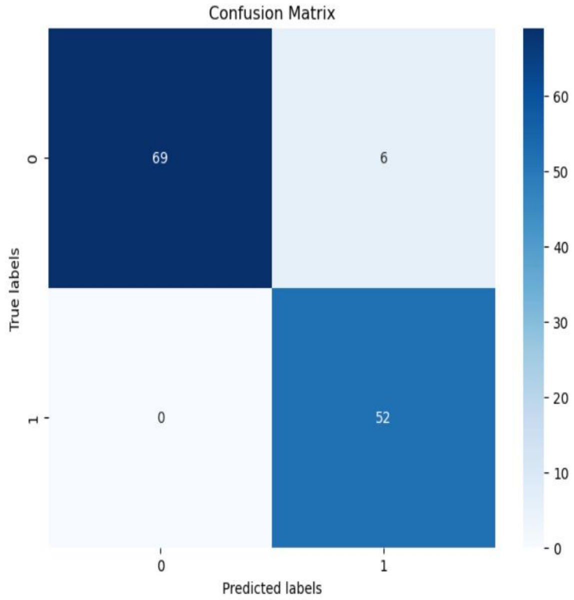

Fig 7: Confusion matrix for model (VGG19)

6. CONCLUSION & FUTURE WORK

In conclusion, our approach multi layered CNN Architecture VGG19 for gender detection yielded an impressive accuracy rate of 99%. Despite the computational demands associated with processing a large dataset, the model demonstrated robust performance. While the extended training time due to the dataset size posed a challenge, the resulting high accuracy justifies the investment. This underscores the efficacy of our method in accurately identifying gender from facial images. Moving forward, optimizations to streamline training time may enhance efficiency without compromising accuracy. Overall, our findings highlight the potential of leveraging deep learning models like VGG19 for gender detection tasks, particularly when confronted with extensive datasets. Future work in gender detection using VGG19 entails data augmentation, hyperparameter tuning, bias mitigation, and real-time video integration. Fine-tuning with transfer learning from ImageNet can enhance accuracy and broaden applicability, while simplifying architectures may improve performance. Generalization across diverse populations and ethical considerations are vital, advancing gender detection for surveillance, human-computer interaction, and marketing analytics.

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