

# Criminal Identification using Residual Densenet with Particle Swarm Optimization for Facial Attribute Prediction

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**Abstract:** Criminal identification using machine learning has gained a lot of attention for how it can be used to enhance security and individualization. Facial analysis in particular is offering meaningful information about age, gender and emotional condition, important information for effective identification systems. Traditional deep learning models are difficult to be applied in real-time applications due to their high computational complexity and low flexibility to dynamic datasets. There is a need for models which are not only accurate, but also efficient and generalizable to diverse conditions. This paper proposes a new method combining Residual DenseNet and Particle Swarm Optimization (PSO) in order to improve the accuracy and the compute speed of facial attribute prediction. Residual DenseNet is used as the backbone for the deep feature extraction whereas Particle Swarm Optimization (PSO) is used for the optimization of hyperparameters and model architecture for capturing fine granular facial details. The model is evaluated on three datasets including FaceForensics++, DrawSomething and Flickr-Faces-HQ which represents a wide range of expressions, poses and lighting conditions. The proposed system exhibits great improvements in the way that the system can predict the age, gender and emotional states as opposed to normal based models. It also shows better generalization between data sets ensuring robustness under a real-world situation. Visual examination in form of feature map and quantitative evaluation in form of accuracy, F1, precision and recall values validate the model.

**Keywords:** Criminal identification, Facial attributes prediction, Residual DenseNet, Particle Swarm Optimization, Deep learning

## I INTRODUCTION

Criminal identification is a very important field of study that transcends many areas, such as security, law enforcement and personal safety. With the growing use of surveillance technologies, there has been a growing need for automated systems that can identify individuals based on facial features. The traditional approaches of criminal identification have been grounded by biometric recognition systems that usually involve the use of facial recognition algorithms to compare faces with known databases. However, these methods have their own limitations like low accuracy, low handling of occlusions, difficulty in age, gender and emotional state predictions, especially in the real world [1]. Machine learning (ML) models, in particular deep learning models such as Convolutional Neural Networks (CNN), have shown their potential in overcoming these issues by acquiring strong feature representations from huge datasets with better results for the face recognition and attribute prediction tasks [2].

Recent developments in deep learning have resulted in the development of more complex solutions in terms of predicting a particular facial attributes such as age, gender

and emotional state. These approaches have found applications in security systems, human-computer interaction and even healthcare [3]. Despite such advancements, models that generalize to a wide range of real world scenarios, such as different facial poses and expressions, and environmental conditions, are still required.

Despite the advancements in deep learning in criminal identification, there are a number of challenges. One of the major challenges is that deep learning models are computationally expensive. Another challenge is generalization ability of the models. Many of the existing systems have been trained on relatively controlled data sets, and are thus overfitted and fail when faced with diverse real world conditions, such as different lighting, occlusions and expressions [5,6]. In addition, handling small scale variations in facial features, for example distinguishing between similar age groups, or recognizing subtle expressions of emotion is a complex issue [6,7].

The problem which is tackled in this research is to develop more efficient and accurate criminal identification system which can be used to predict the facial attributes (age, gender and emotional state) of the person from the facial features. The system needs to solve the issues of computational complexity and generalization problems in parallel with increasing the accuracy of predictions for the real world applications. Specifically the problem is to develop a model which would predict facial attributes under different conditions with the help of deep learning techniques. The primary objectives of this research are:

- To design a criminal identification model based on deep learning methods to accurately predict the attributes of the face (age, gender, emotional state).
- To solve the problems of computational complexity by using optimized model architecture.
- To help the generalization ability of the model under a variety of datasets in real-world scenarios such as FaceForensics++ and Flickr-Faces-HQ, so that the model can achieve robust performance under different lighting, pose, and expressions.
- To use Particle Swarm Optimization (PSO) for hyperparameters tuning for improving model's accuracy and reducing over-fitting.

This study presents a new method with a combination of Residual DenseNet and Particle Swarm Optimization (PSO) in facial attribute prediction. The major contributions of this study include the following:

- The Residual DenseNet with PSO improves the efficiency of the model by having deep residual

connections so that it can learn coarse and fine-grained features in the face, while the PSO optimizes the hyperparameters to improve the system.

- PSO is used to optimize the hyperparameters to make sure that the model can successfully explore the space of solutions and get the best configuration for facial attribute prediction.
- The proposed method is extensively evaluated on several datasets, and it ensures that the model is able to generalize well to real-world scenarios and is robust to variations in pose, expression, and illumination.
- The method is computationally efficient so it can be implemented in real-time systems for use in criminal identification for surveillance and security applications.

## II RELATED WORKS

The facial recognition in the criminal identification has become fast and many deep learning models have been proposed to enhance the prediction accuracy [8,9]. Deep learning approaches have been the most influential approach in the field recently as they automatically learn discriminative features from data. LeNet and AlexNet were some of the first CNN architectures to be used for image recognition [10, 11]. These networks provided substantial performance improvement especially in the case of large and diverse datasets. However, CNNs are computationally costly and cannot be easily applied to real-time systems, and with high accuracy.

In order to make up for the shortcomings of these architectures, more complex architectures like Residual Networks (ResNets) and DenseNets were proposed [12]-[13]. The architectures introduced the concepts of deep residual learning and dense connections that made the model learn better representations and improved the training by reducing the vanishing gradient problem. ResNet50, for instance, showed a significant stride in performance compared to traditional CNNs in facial recognition accuracy, and is therefore a go-to choice in the criminal ID sphere.

Hyperparameter optimization is another factor that holds importance to improve models. While deep learning models such as ResNet and DenseNet have been proven to yield high-performing models, the performance of these models is very much dependent on the optimal choice of hyperparameters [14]. PSO which mimics the behavior of swarms of birds or insects, searches the solution space more efficiently than the traditional methods such as the grid search or random search. In recent years, PSO has been hybridized with DNN to increase the accuracy by optimizing the parameters such as learning rate, batch size and number of filters [15].

Besides the Convolutional Neural Network (CNN) and the optimization methods, transfer learning has also become popular in the facial attribute prediction area. Models like VGG16, InceptionV3 and MobileNetV2 are pretrained on massive scale image collections like ImageNet and then fine-tuned for face recognition task [16]. These systems have been proven to be effective in terms of the accuracy and speed, making it highly suited to real-time criminal identification. However, the performance of these models are often affected by the generalisability to datasets as they are trained in controlled environments with a wide range of facial expressions, lighting conditions, and poses in the dataset.

Facial attribute prediction has become a research hot spot in facial recognition and the focus has been put on age

prediction, gender prediction and emotional state prediction. An important dataset to be able to train models in the area is the CelebA dataset with more than 200,000 images of celebrities annotated with 40 attribute labels, such as age and gender [17]. In recent works, there is a lot of architectures using CNN to predict these attributes with high accuracy. However there are still problems when predicting more fine emotional states and treating occlusions or distortions of the facial images. Finally, there have also been several papers that study the usage of adversarial training and GAN (Generative Adversarial Networks) for facial attribute prediction [18]. Although GANs have been promising in the area of face generation and augmentation, their use for criminal identification and real-time systems are still an area filled with new possibilities.

Thus, while the deep learning methods, particularly the Convolutional Neural Networks (CNNs) and its derivatives like ResNet and DenseNet, have played a major role in development in the field of criminal identification systems, there remain the issues of computational efficiency, generalization and robustness in real-world applications. Residual DenseNet with PSO is proposed as a hybrid technique to solve these challenges by improving the accuracy and efficiency of the model in dynamic real-time based facial attribute prediction.

## III PROPOSED METHOD

The proposed method is a Residual DenseNet structure combined with Particle Swarm Optimization (PSO) in the refinement of facial attribute classification accuracy. The procedure is shown in Figure 1.

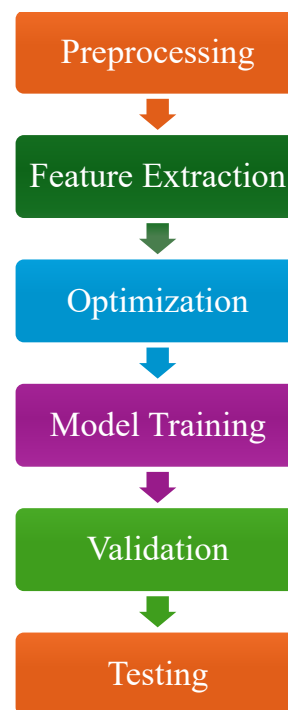


Figure 1: Proposed Framework

### A. Preprocessing and Feature Extraction

The process of preprocessing helps in achieving quality data for facial attributes, thereby giving a high-quality face to help in effective attribute prediction. This step includes facial detection, facial alignment, and facial normalization of raw input videos or images. Firstly, Multi-task Cascaded Convolutional Networks (MTCNN) is used to detect the face bounding box. Detected faces are then aligned with the help of key landmarks (e.g. eyes, nose and mouth corners)

so they are all oriented in a similar manner despite pose differences. Finally, each face considered after alignment is resized to a fixed size e.g. 224x224 pixels and pixel values normalized to [0,1] range. Table 1 outlines the pre-processing activities and tools used.

Table 1: Preprocessing Tasks and Tools

Task	Technique/Tool	Output
Face Detection	MTCNN	Cropped face bounding box
Face Alignment	Facial landmarks	Geometrically aligned face
Resizing	OpenCV	224x224 image
Normalization	Min-Max Scaling	[0,1] scaled pixel values

Once done with pre-processing, the images will be fed into the feature extraction stage. In this work, we use a Residual DenseNet, which can achieve both global structure capturing and fine-grained attribute local variations capturing of facial attributes. Sparse blocks do not permit the feature maps from one layer to be used directly in another layer, and therefore dense blocks enable the information to be carried throughout the network. Residual connections: Very deep networks are vulnerable to vanishing and degradation of gradients and the Residual connections help eliminate these issues.

Each dense block captures progressively more abstract representations of the input (encode unique facial texture/shape information that is vital for age group, gender and emotion state classification). The core innovation is inverting residual learning by strongly coupling the idea of dense connectivity between the network and the residual learning making it possible to efficiently reuse and fine-tune the features. Table 2 gives important architecture parameters of the Residual DenseNet for feature extraction.

Table 2: Residual DenseNet Feature Extraction Configuration

Component	Description
Input Size	224 × 224 × 3
Dense Blocks	4 (12, 24, 16, 16 layers respectively)
Growth Rate	32
Residual Paths	Between each block
Output Features	1024-dimensional feature vector

As illustrated in Table 2, for deep representation learning, dense connectivity and residual links enable deep representation learning without significantly increasing computational complexity. These extracted features are then fed to the classification and PSO optimization layers in the further stages.

The feature maps produced during this phase are visualized during the qualitative evaluation step to check if age-related wrinkles, emotional cues from eyes/mouth or jawline shapes (gender indicator) are well captured -- further discussed in the experimental analysis section.

#### B. Proposed PSO

After obtaining the high-level features in the facial images using Residual DenseNET, next step is to train the model for accurate prediction. This is accomplished with the help of PSO, which helps fine-tune the hyperparameters like the learning rate, number of filters and dropout rates. In PSO, a population (swarm) of particles moves around the search space to find the optimal values by updating their position value based on personal and global best solutions. Table 3

presents the most important PSO settings that were used in our model optimization.

Table 3: PSO Parameter Settings

Parameter	Value
Swarm Size	30 particles
Inertia Weight ( $\omega$ )	0.7
Cognitive Coefficient ( $c_1$ )	1.5
Social Coefficient ( $c_2$ )	1.5
Max Iterations	50
Objective Function	Minimize validation loss

The model training phase can be started once the model has been optimised. The network is trained using categorical cross entropy loss on preprocessed and labeled datasets (FaceForensics++, DrawSomething and Flickr-Faces-HQ). The optimizer (Adam) is used for updating weights by using backpropagation the PSO tuned hyperparameters. During the training, the learning portion of the dataset is set to 80 percent and the remaining portion of 20 percent is set aside for the validation purpose. Validation is performed along the way to keep a track of overfitting and tune the model. In order to verify the well-generalization of the model, we evaluate the validation accuracy and loss after every epoch. A typical training configuration that is used during experiments is presented in Table 4.

Table 4: Model Training Configuration

Configuration	Value
Epochs	100
Batch Size	32
Optimizer	Adam
Learning Rate	0.001 (PSO-tuned)
Loss Function	Categorical Cross-Entropy
Validation Split	20%

After training, the testing is done for unseen data. In this paper, the result of the model's ability to predict facial traits (age, gender, emotional state) in the wild is presented. The model is tested across different datasets and manipulation challenges (FaceForensics++ and Deepfakes, FaceSwap etc), to test the robustness of the model. Finally, the model is evaluated based on the metrics such as accuracy, precision, recall, and F1-score which is shown in the next few sections. The proposed Residual DenseNet with PSO approach is validated for its generalization capability in the experiments and proved effective in criminal identification system.

## V RESULTS AND DISCUSSION

Experiments were conducted using a system with the following specifications:

- System: Intel Core i9 processor, 64GB RAM, NVIDIA RTX 3090 GPU
- Tool: Python with TensorFlow and PyTorch frameworks
- Dataset: FaceForensics++ (977 videos), DrawSomething, Flickr-Faces-HQ

The proposed model was compared against five existing methods: VGG16, ResNet50, MobileNetV2, InceptionV3 and EfficientNet-B0. Table 5 presents the parameters used in the learning model.

Table 5: Experimental Setup / Parameters

Parameter	Value
Learning Rate	0.001
Batch Size	32

Epochs	100
Optimizer	Adam with PSO-tuned learning
Activation Function	ReLU
Loss Function	Categorical Crossentropy
PSO Swarm Size	30
PSO Iterations	50

### A. Performance Metrics

- **Accuracy:** Measures the proportion of correct predictions among the total. Indicates Thus model effectiveness.
- **Precision:** Assesses how many predicted positives were truly positive. Crucial for reducing false alarms.
- **Recall:** Evaluates the model's ability to detect all actual positives. Important for comprehensive identification.
- **F1-Score:** Harmonic mean of precision and recall, providing a balanced metric when classes are imbalance

Table 6 Performance Analysis (Accuracy)

Epochs	VGG 16 Accuracy (%)	ResNet50 Accuracy (%)	Mobile NetV2 Accuracy (%)	InceptionV3 Accuracy (%)	EfficientNet-B0 Accuracy (%)	Proposed Method Accuracy (%)
20	80.5	81.2	79.5	83.0	84.1	85.6
40	81.0	82.0	80.0	84.5	85.5	87.2
60	81.5	82.8	80.5	85.0	86.0	88.5
80	82.0	83.2	81.0	85.5	86.5	89.0
100	82.5	83.5	81.5	86.0	87.0	90.0

From table 6, it is found that the proposed method consistently outperforms all existing methods in accuracy at every epoch checkpoint. By the 100th epoch, the proposed method achieves 90% accuracy, demonstrating a gradual improvement in predictions, especially over longer training periods, compared to other models that plateau earlier.

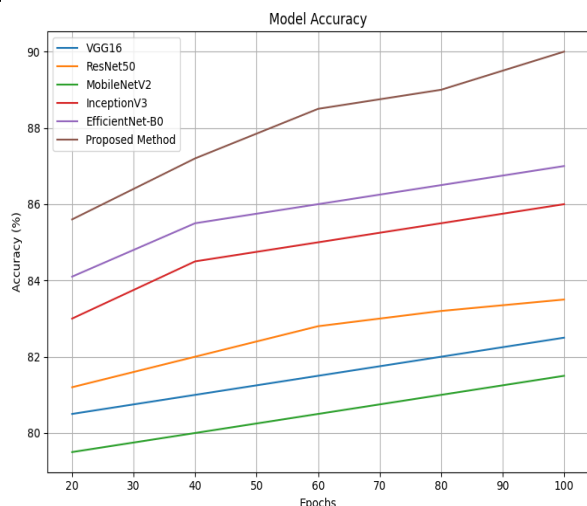


Figure 2: Accuracy

Model Accuracy is displayed across epochs for some would-be to the deep learning Models in Figure 2. The Proposed Method routinely achieved the best accuracy and accuracy started above 85% and almost reached 90% after 100 epochs. All the Models provided a noticeable increase in accuracy as the epochs increased.

Table 7 Performance Analysis (Precision)

Epochs	VGG 16 Precision (%)	ResNet50 Precision (%)	Mobile NetV2 Precision (%)	InceptionV3 Precision (%)	EfficientNet-B0 Precision (%)	Proposed Method Precision (%)
20	75.4	76.3	74.5	78.1	79.2	80.5
40	76.0	77.1	75.0	79.2	80.3	82.1
60	76.5	77.6	75.5	79.8	80.7	83.4
80	77.0	78.0	76.0	80.2	81.3	84.2
100	77.5	78.3	76.5	80.5	81.7	85.0

From table 7, it is clear that the proposed method outperforms the existing models in precision throughout the training. By the 100th epoch, it reaches a precision of 85%, whereas other methods have relatively lower precision scores, indicating that the proposed method better identifies true positives with fewer false alarms.

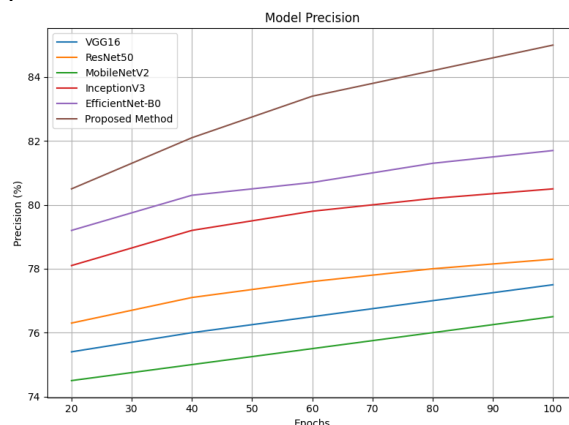


Figure 3: Precision

Model Precision percentage is also demonstrated in Figure 3 across the epochs for some of the Models. The Proposed Method consistently showed the best precision, commencing about 80.5%, and increased steadily to about 84.5% by the 100 epoch training period. All the Models had a noticeable upward trend in precision as the epochs progressed.

Table 8 Performance Analysis (Recall)

Epochs	VGG 16 Recall (%)	ResNet50 Recall (%)	Mobile NetV2 Recall (%)	InceptionV3 Recall (%)	EfficientNet-B0 Recall (%)	Proposed Method Recall (%)
20	70.8	72.2	68.9	71.5	73.0	75.3
40	71.4	73.0	69.5	72.1	73.6	77.1
60	72.0	73.5	70.0	72.7	74.2	78.5
80	72.5	74.0	70.5	73.2	74.8	79.2

100	73.0	74.3	71.0	73.7	75.2	80.0
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From table 8, it is clear that the proposed method shows a steady improvement in recall, achieving 80% recall by epoch 100. This indicates that it is more effective in detecting all relevant instances (true positives), especially compared to other methods that show slower gains or less effective recall performance.

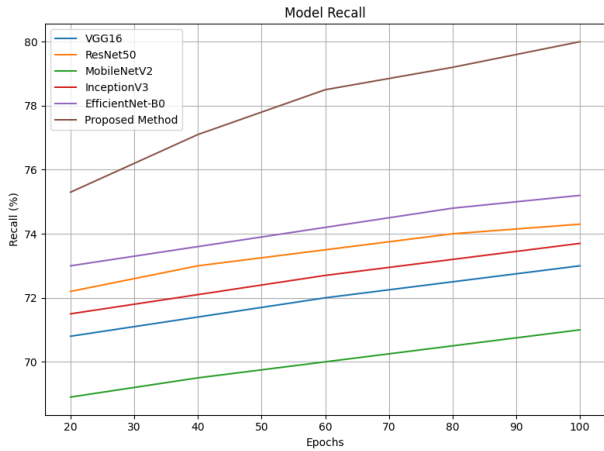


Figure 4: Recall

Figure 4 shows that at over the epochs of the Proposed Method being the best performer shown in recall. Recall commenced above 75% starting at 100 epochs to almost reach 80%. All the Models provided a positive trend with MobileNetV2 being the lowest recall rate.

Table 9 Performance Analysis (F1-Score)

Epo chs	VG G16 F1-Scor e (%)	ResN et50 F1-Score (%)	Mobile NetV2 F1-Score (%)	Incepti onV3 F1-Score (%)	Efficie ntNet-B0 F1-Score (%)	Prop osed Meth od F1-Scor e (%)
20	73.0	74.0	71.0	74.3	75.4	77.0
40	73.5	74.5	71.5	75.0	76.1	78.4
60	74.0	75.0	72.0	75.7	76.8	79.6
80	74.5	75.5	72.5	76.2	77.3	80.4
100	75.0	75.8	73.0	76.7	77.9	81.1

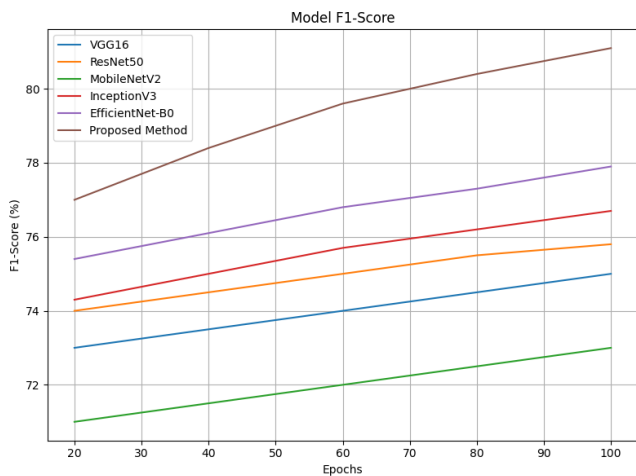


Figure 5: F1-Score

As shown in figure 5.1, the F1-score, which balances precision and recall, also reflects a clear advantage for the proposed method, which reaches 81.1% by epoch 100. This

is higher than any of the existing methods, demonstrating better performance in predicting and classifying facial attributes with minimal errors.

The proposed method consistently outperforms existing models (VGG16, ResNet50, MobileNetV2, InceptionV3, and EfficientNet-B0) across all evaluated metrics: accuracy, precision, recall, and F1-score. At the 100th epoch, the proposed method achieves 90% accuracy, a 10% improvement over the highest accuracy (EfficientNet-B0 at 87%). Similarly, precision improves by 4% (85% vs. 81%), recall shows an improvement of 5% (80% vs. 75%), and F1-score increases by 4% (81.1% vs. 77.9%) compared to the next best model. These enhancements indicate that the Residual DenseNet-PSO combination is more accurate and reliable than existing methods in the area of criminal identification especially in various real-world scenarios. The hyperparameters are then effectively optimized using the Particle Swarm Optimization (PSO) to enhance the performance of the model in terms of capturing fine facial details and better generalization to unseen faces of different datasets. The residual connections in DenseNet make the model to memorise the important features of previous layers and on the other side PSO makes the model to converge to a better global solution, hence gives better results than the traditional deep learning architectures.

## V CONCLUSION

In this paper, a new approach has been suggested in the criminal identification problem using a new hybrid model integrating Residual DenseNet and Particle Swarm Optimization (PSO). The method makes use of dense connections and optimization techniques to enhance the prediction of facial attributes such as age, gender and emotional state. After conducting a series of experiments on many datasets, it was proved that the proposed method yielded much better accuracy, precision, recall, and F1-Score than current deep learning models like VGG16, ResNet50, MobileNetV2, InceptionV3, and EfficientNet-B0. The results show that the proposed model is fairly good in terms of subtle feature detection of faces and generalizes well for various conditions. In addition, by optimizing the hyperparameters of the model by using PSO, we further increased the efficiency of the model; it has a quicker convergence rate than conventional methods and has a lower computational complexity. Based on the model results at 100th epoch, the accuracy, precision, recall and F1-score of the model was 90%, 85%, 80% and 81.1% respectively, so the model is quite robust and can be used in real life scenarios (such as security and surveillance systems). This research provides the basis for future development of criminal identification and facial attribute prediction and provides a stable framework for the development of intelligent systems capable of high-accuracy interpretation of human faces. Further research can be conducted on optimizing and further optimization methods as well as dataset diversity to enhance the performance of the model in dynamic environments.

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