

## SRI VENKATESWARA COLLEGE OF ENGINEERING

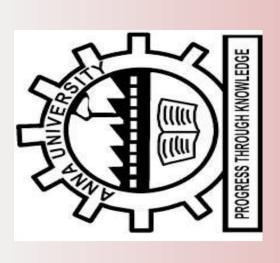
# DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING

## Gender And Ethnicity Identification System Facial Features Based Human Age,

Dr. S. Veluchamy, M.E., Ph.D. Department of ECE Assistant Professor, Project Supervisor:

YEAR PROJECT **JUNE 2022 UG FINAL** 

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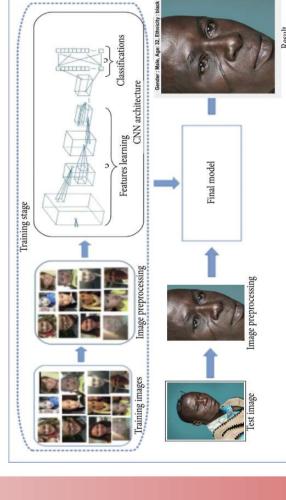
#### Abstract

В Since the rise of social platforms and social media, automatic age, ethnicity, and gender classification have been relevant to

growing number of applications.

- Nevertheless, the performance of existing methods on real-world images is still significantly lacking.
- convolution neural networks (CNN) can result in a considerable As a result, we show that learning representations using deepimprovement in performance on these tasks.
- For image-based gender, age, and ethnicity estimates, deep neural networks with pre-trained weights are used.
- Finally, a hierarchy of deep CNNs is explored, which first classifies participants by gender and then predicts age and ethnicity using separate models. VGG is used to investigate transfer learning.

### Project Workflow



#### Modules

Primary modules used in this project are:

some ➤ Image Pre-processing: Iimproves the image data (features) by suppressing unwanted distortions and enhancement of important image features.

trained from scratch for facial recognition using VGG Face Dataset.

VGG16 is a convolution neural net (CNN) architecture which is

Proposed Architecture Diagram

- the segmentation of the image and identifying the position of the ➤ **Detection**: Refers to the localization of an object which means object of interest.
- to a particular class and that will, later on, help the model to differentiate between different classes. This process where the model learns the features from the dataset is called model > Feature extraction and training: Identifies the most interesting patterns of the image, features that might be unique

13 +13 ×312

41 × 512

20

Relu2\_1

Relu1\_1

Conv2\_2 112

onv1\_2

Relu5\_2

50 413

Relu2\_2

Relu1\_2 Pool1:k2s2

Relu4\_3 Pool4:k2s2

Relu3\_3 Pool3:k2s2

Pool2:k2s2

Pool5:k2s2

,13 13 512

50 1 256

Juv2\_1

Com/1\_1 200

Image size 200

Conv\_5

Conv\_4

Com5\_113

Conv4\_125

Comv3\_150

Relu5\_1

Conv5\_2

JNV3\_2

√128 √128

> Classification: Categorizes detected objects into predefined classes by using a suitable classification technique that compares the image patterns with the target patterns.

## Hardware and Software

Software:

- Windows 11 ➤ Operating System

Here we use, Convolution layer of 3x3 kernel ,stride 1x1 and padding(1),starting with 200x200 input features. Max pool layer of 2x2 pool size and stride 2x2 and has no zero padding of the system. We use the below formula to determine the number of output

Hardware:

- Pentium -IV - 2.4 GHZ -8 GB ➤ Processor Type ➤ Speed

convolution padding size convolution kernel size convolution stride size

p: S:

 $n_{out}$ : number of output features

nin: number of input features

+1

 $|n_{in} + 2p - k|$ 

 $n_{out} =$ 

features from each layer.

System Used:

## Requirements

- MATLAB R2022a > Software Programming Package

- 552 GB SSD ➤ Hard disk

➤ Name of the Company: MI ➤ Version: 21H2

### Implementations

AGE







RACE

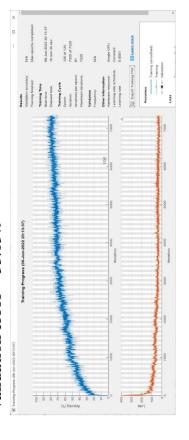


## Conclusion and Future works

- The proposed approach utilizes a superior system performance in order to increase the estimation accuracy of demographic variables.
- It demonstrates that the suggested facial features-based Gender, Age, and Ethnicity estimation outperforms the majority of stateof-the-art techniques in UTK databases.
- In addition, the proposed method performed admirably in the difficult databases.
- In future different optimization and regularisation functions can be incorporated to the proposed system to increase the accuracy and also decrease the false prediction rate.

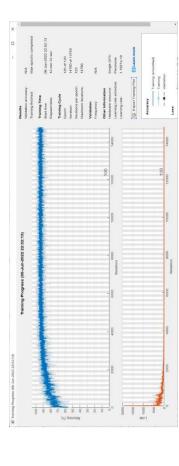
#### Graphs

Validation error - 33.13% Training accuracy - 81%



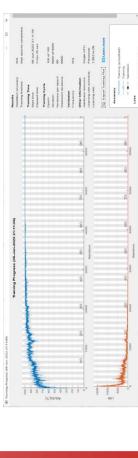
#### GENDER

Validation error - 8.16%Training accuracy - 91%



Training accuracy -98 %RACE

Validation error - 3.06%



#### References

N. Kumar, A. Berg, P. Belhumeur, and S. Nayar. (2021), "Describable visual attributes for face verification and image search." IEEE Trans. PAMI, 33(10):1962–1977, 2021.

Zhuang, Z., Landsittel, D., Benson, S., Roberge, R., Shaffer, R. (2019), "Facial anthropometric differences among gender, ethnicity, and age groups." Annals of Occupational Hygiene (2019)