

Facial Demographics

Mentor: Tanisha Bhayani

HR: Akanksha Goplani

PS Instructor: Prof. Aruna Malapati

Group Members:

1. Ashutosh Sharma (2018B3A70928P)
2. Shreyansh Joshi (2018A7PS0097G)
3. Vikas Sheoran (2018B3A70847H)
4. Jash Shah (2018A8PS0507P)



About Project

- Our project was Facial Demographics.

(predicting the *gender* and *age* of a person given his/her face image)

- This is accomplished using Machine Learning / Deep Learning techniques such as CNNs.
- Different students were asked to work on different approaches –
 1. **Designing CNN architecture from scratch**
 2. **Transfer Learning with CNN and ML Models**
 3. **Core ML models such as SVMs**

Contents

1. Introduction to Facial demographics
2. Project Outlines
3. Methodology
4. Conclusion and the Way forward



What is Facial Demographics ?

- Facial demographics, essentially refers to taking facial images as input , preprocessing it, and extracting useful information from faces using Machine Learning / Deep Learning techniques.
- Analyzing different features of a person from face such as gender, age, race are a part of facial demographics.



Weekly Outline

Week 1 : Familiarization with Deep Learning and Facial demographics by reading 6 research papers provided by mentor.

Week 2 : Choose Dataset and performed EDA on the dataset, to understand data distribution as well as know more about the given dataset.

Week 3: Basic model for gender and age classifier, that classifies gender and age into 2 and 5 classes respectively.

Weekly Outline

Week 4 : Continue implementation of age and gender classification, trying to get above the baseline and improve accuracy.

Week 5 : Jump onto age estimation, trying to predict exact ages. Try using another dataset and perform EDA on it as well and then perform age estimation on it.

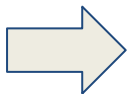
Week 6: Optimise the model to its best, and benchmark its performance. Finally, design a script (pipeline) , so that it can be deployed as an end-to-end model in real world.

Project Methodology

Literature Review

Research Paper	Author(s)
Gender Classification Techniques: A Review	Preeti Rai and Pritee Khanna
Face Recognition Performance: Role of Demographic Information	Brendan F. Klare, Mark J. Burge, Joshua C. Klontz, Richard W. Vorder Bruegge, Anik K. Jain
Face Recognition and Age Estimation implications of Changes in Facial Features: A Critical Review Study	Rasha R. Atallah, Amirrudin Kamsin, Maizatul A. Ismail, Sherin A. Abdelrahman, Saber Zerdoumi
Age estimation via face images: A Survey	Raphael Angulu
Convolutional Neural Networks for Age and Gender Classification	Ari Ekmekji
Efficient facial representations for age, gender and identity recognition in organizing photo albums using multi-output ConvNet	Andrey V. Savchenko

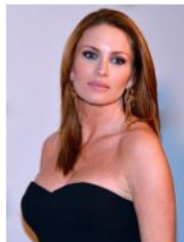
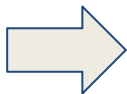
Dataset used:



23,708 Images

Wikipedia

Other
Dataset used:



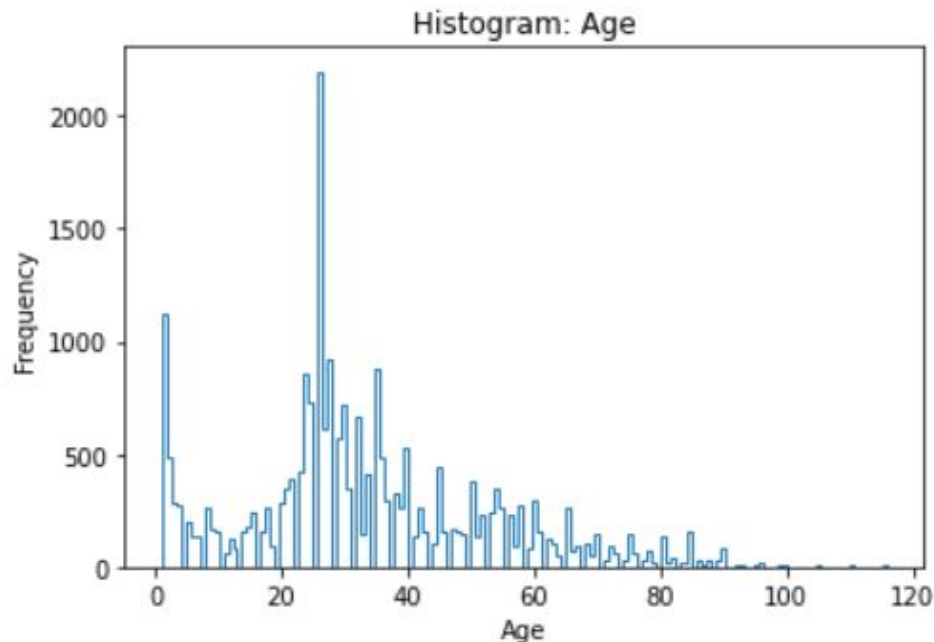
62,308 Images

EDA (Exploratory Data Analysis)

- EDA refers to the critical process of analyzing data sets so as to discover patterns, spot anomalies, summarize their main characteristics with the help of summary statistics and graphical/visual methods.
- It was done to understand the data first and try to gather as many insights from it. EDA helped us in making sense of data in hand, before we got our hands dirty with it.



Some examples of the meta data analysis we did.....



Histogram of the dataset (Frequency vs Age)

```
Female_Age.describe()
```

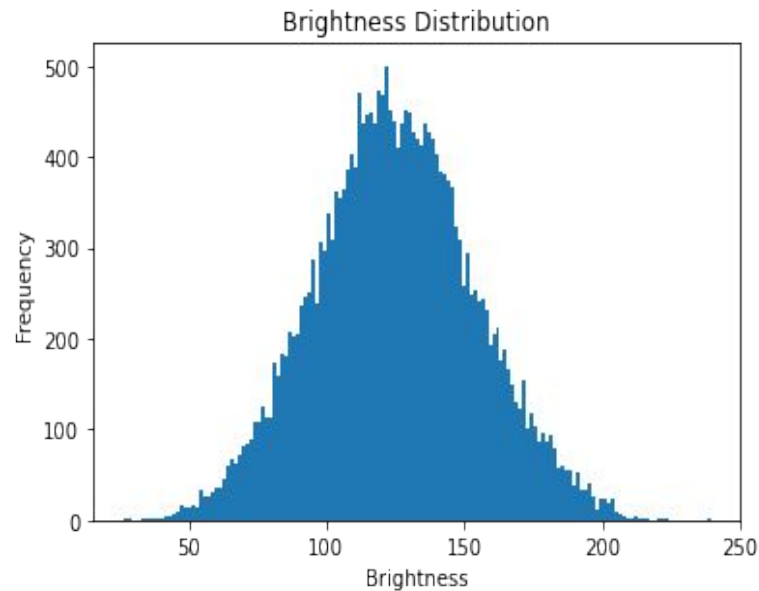
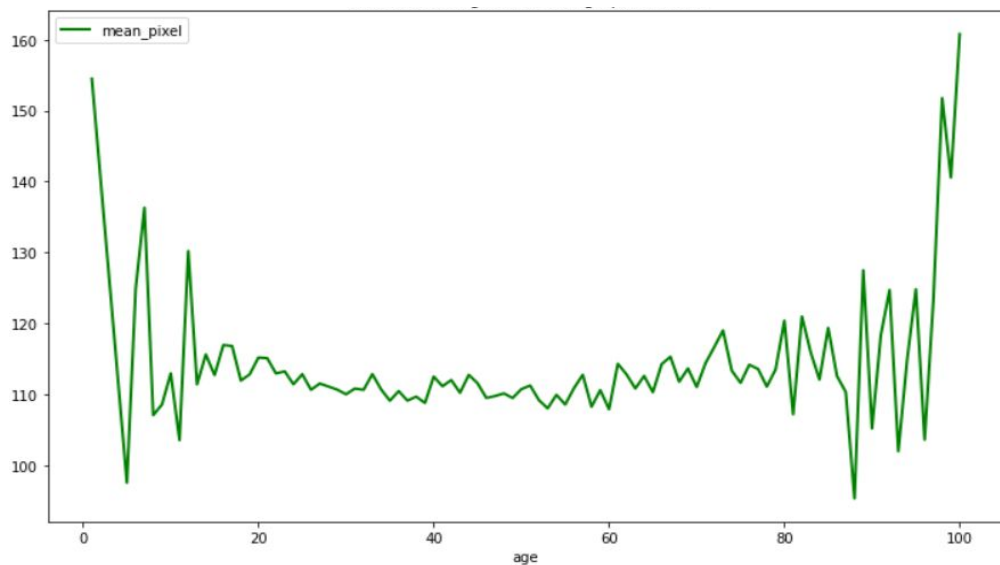
```
count    11314.000000
mean      30.678186
std       19.752001
min        1.000000
25%       21.000000
50%       26.000000
75%       37.000000
max      116.000000
Name: Age, dtype: float64
```

```
Male_Age.describe()
```

```
count    12391.000000
mean      35.695666
std       19.705223
min        1.000000
25%       25.000000
50%       34.000000
75%       50.000000
max      110.000000
Name: Age, dtype: float64
```

Descriptive Statistics of the dataset
for male and female

Some examples of the pixel-based EDA we did.....



Convolutional Neural Network (CNN)

- CNN is a very popular and robust way of dealing with images. It is primarily used for extracting features (higher representations) from the image, which are then fed into a FC layer for classification tasks.

Age & Gender Classifier (UTKFace dataset)

- Input shape - 198 x 198 x 3
- Classifies age into 5 categories in gaps of 25 years, and gender into male/female.
- Predict age & gender at once -> Multi-output classification
- Loss functions for both age & gender - *categorical_crossentropy*, optimizer - *Adam*
- Used *LearningRateScheduler* of keras, with initial lr of 0.008 & trained the model for 44 epochs.
- Model was trained on 23,708 images.

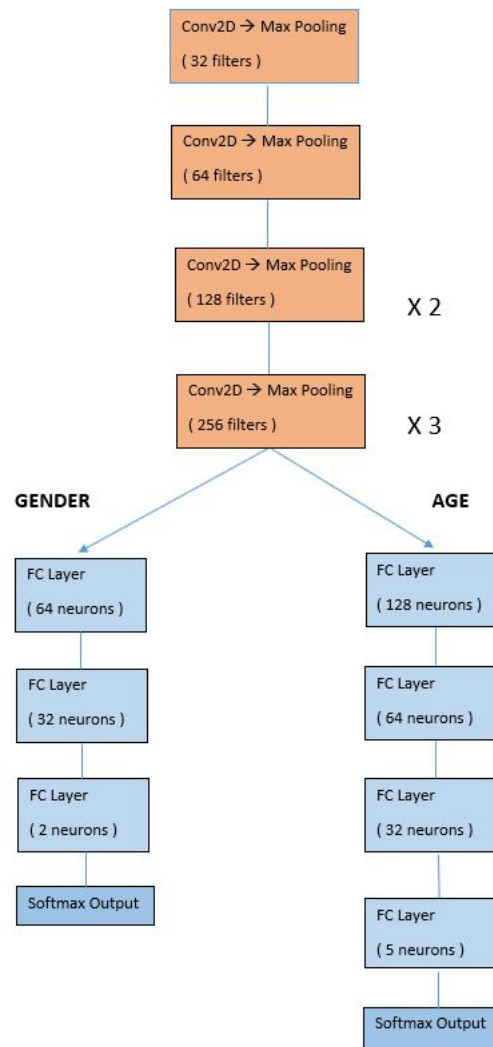
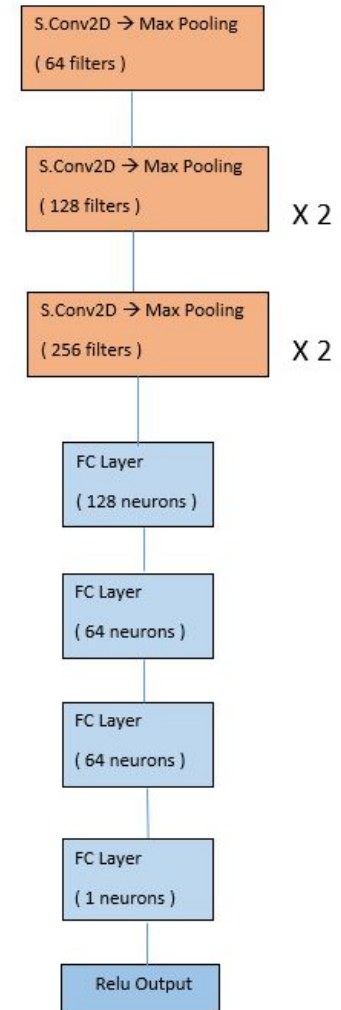


Table : Results for age & gender classifier

TRAIN_LOSS	TRAIN_AGE_ACC	TRAIN_GENDER_ACC	VAL_LOSS	VAL_AGE_ACC	VAL_GENDER_ACC
1.8366	0.6626	0.9092	2.1247	0.6329	0.8745
0.7485	0.9103	0.9571	1.6166	0.7042	0.8798
0.9342	0.8366	0.9319	1.6198	0.7193	0.8806
0.0527	0.9904	0.9912	1.1161	0.7410	0.8978
0.7864	0.8387	0.9931	0.9038	0.7418	0.8851
0.1389	0.9646	0.9944	0.7495	0.8279	0.9502

Age Estimator (WIKI Dataset)

- Input shape - $180 \times 180 \times 3$
- Loss function - *mse* , optimizer - *Adam*
- Metrics - *mae*, *mse*
- LearningRateScheduler was used with an initial lr of 0.006 that halved lr every 12 epochs.
- Model was trained for a total of 95 epochs, in 2 batches - 45 + 50.
- Model was trained on 22,578 images first. Later I tried on 34,200 images as well.



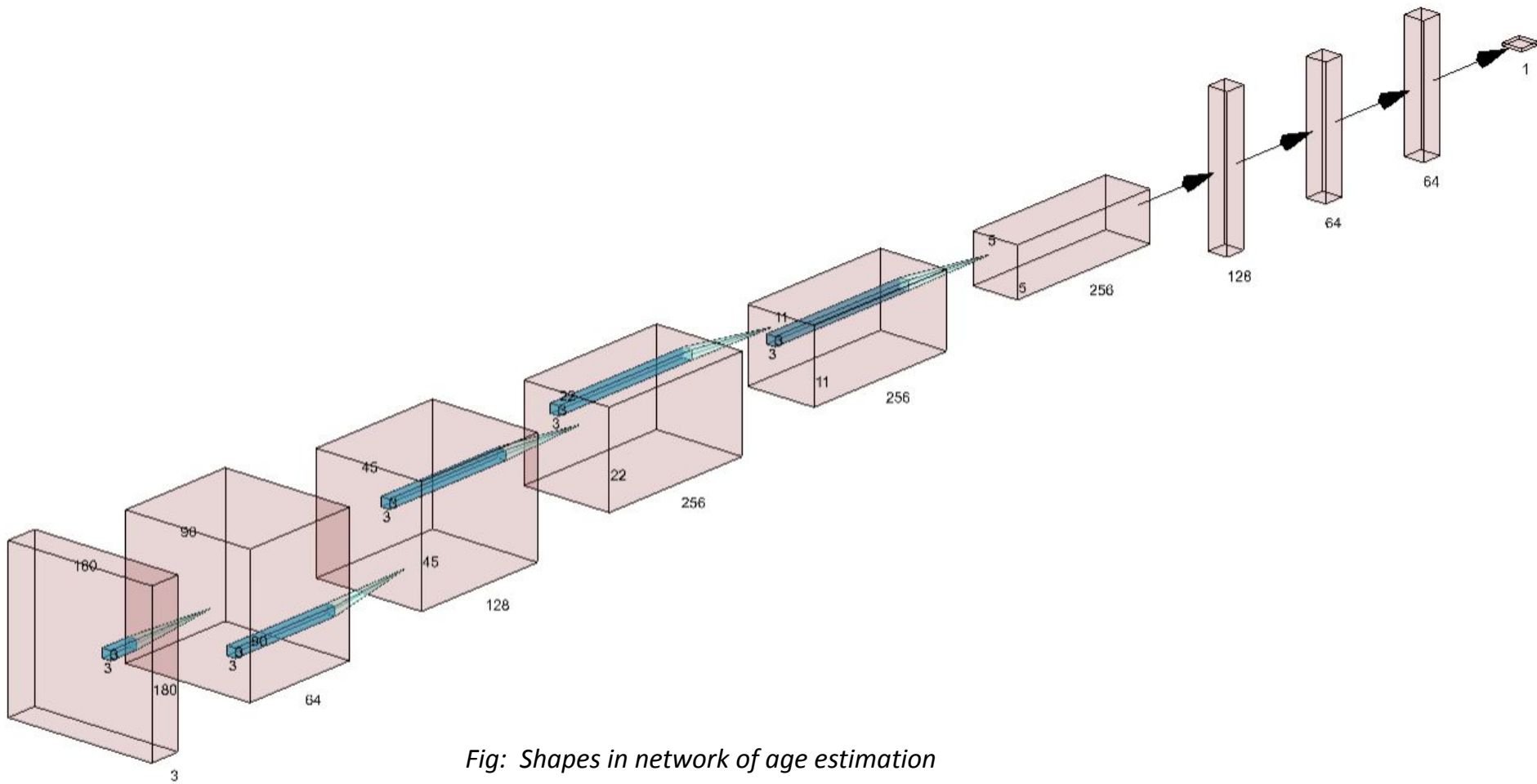


Fig: Shapes in network of age estimation

Table : Results for age estimator

TRAIN_LOSS	TRAIN_MAE	VAL_LOSS	VAL_MAE
177.7641	11.1566	199.3812	11.0324
17.6605	2.9786	83.6385	6.9328
89.6336	7.3960	66.4088	6.2225
58.5194	5.9128	30.8964	5.9402
44.6834	5.1108	44.0836	5.5679

Transfer Learning



Data	Images
Training	20,000
Cross-Validation	1,854
Test	1,854



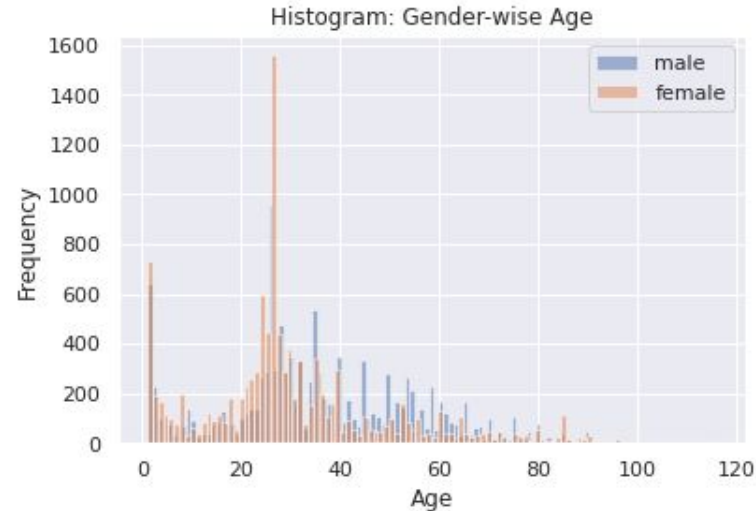
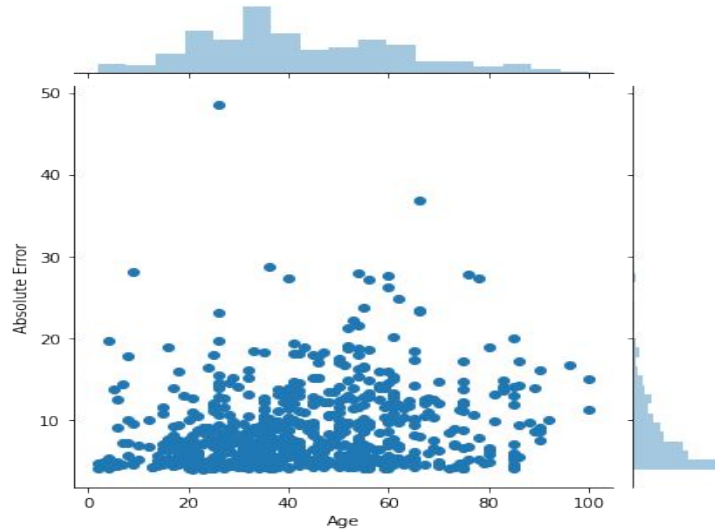
Age prediction as Regression



Model Highlights	Results	Benchmarks
<ul style="list-style-type: none">• 3 Conv + 3 FC layers• SeparableConv2D• SpatialDropout• BatchNorms• Gaussian Noises• Weight Constraints• Dropout• ELU	<p>Model 1: 4.8693623457061745 Model 2: 4.885024872169711 Model 3: 4.862204356220563 Model 4: 4.8670852977201475 Model 5: 4.860798894619208 Model 6: 4.712113978633736 Model 7: 4.677876185933385 Model 8: 4.839006362061724 Model 9: 5.073820527636934</p> <p>Ensemble MAE: 4.620075553157043</p>	<p>Various Papers</p> <ul style="list-style-type: none">• 9.19*• 7.36 (Git Repo)• 5.44 (MobileNet)• 5.39 (CORAL)

Error Analysis

Bad	Good
<ul style="list-style-type: none">• Low Resolution / Unreal• Blacks• Very Old• Wrong Labels	<ul style="list-style-type: none">• High Resolution• Others• 50 or younger



DL > ML ?

- Data and Scalability
 - Computation Power
 - Challenge - Hyperparameter Tuning
 - Grid Search vs Random Search
-
- Data, Assumptions
 - Resources
 - Problem
 - Application
 - Time Constraint - like this.

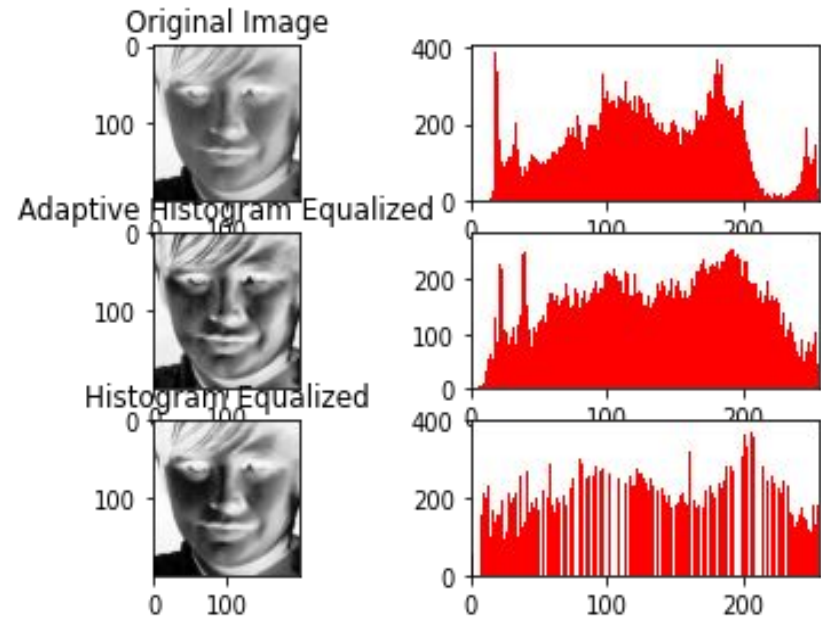
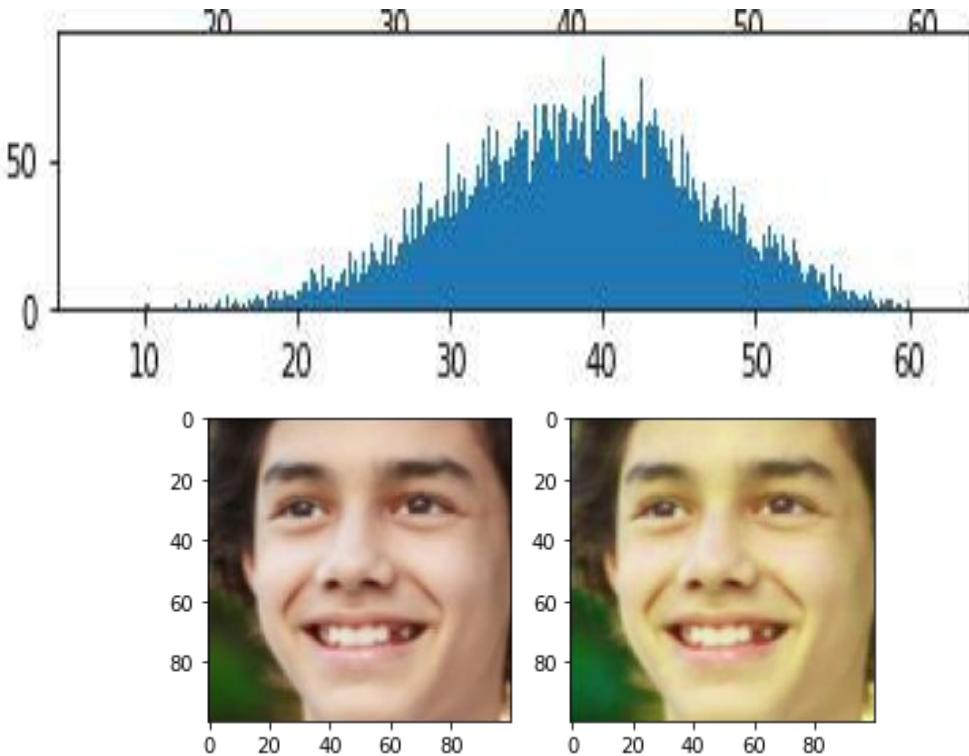
Model	Test
Neural Networks (Regularized)	0.9395
SVC	0.9363538296
LDA	0.9363538296
Voting Classifier - Top3	0.9336569579
QDA	0.9314994606
Stochastic GBoost	0.9309600863
XGBoost	0.9282632147
Bagging	0.9234088457
AdaBoost	0.9234088457
Gradient Boosted Trees	0.9207119741
Random Forest	0.9196332255
LogisticRegression	0.9190938511
Perceptron	0.9190938511
Voting Classifier	0.9174757282
SGDClassifier - Linear SVM	0.9099244876
KNeighborsClassifier	0.9088457389
SGDClassifier - Logreg	0.9034519957
Linear SVC	0.8948220065
DecisionTreeClassifier	0.8759439051

SVM model

The improved model consisted of this basic pipeline of workflow :-

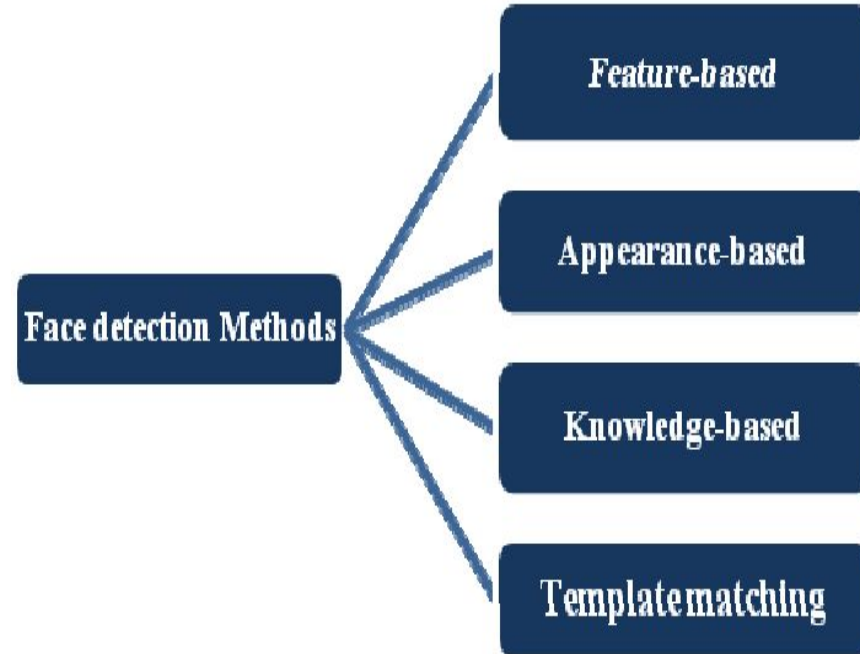
- 1) General EDA - Pixel Level
- 2) Pre-processing techniques
 - a) Face detection and further augmentation
 - b) Feature engineering
- 3) Dimensionality reduction
- 4) Applying SVM and accuracy analysis

Pre-processing methods

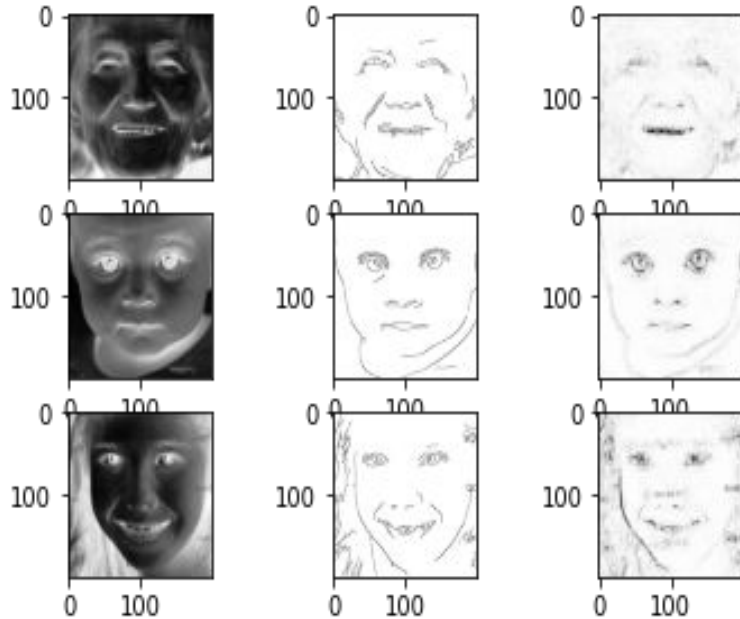


a) Face detection & augmentation

- Viola jones method
 - Haar like features (Feature based)
 - Integral Image
 - Adaboost Cascade (Knowledge based)
- HOG filter was also considered
(Template Matching)
- Linear Binary patterns
(Appearance based)



b) Feature engineering - Model free algorithm

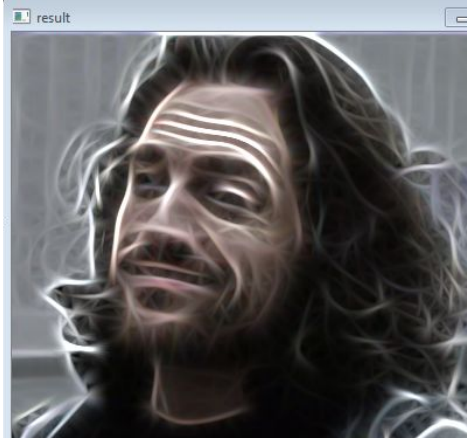


Direct methods - Laplacian and Sobel

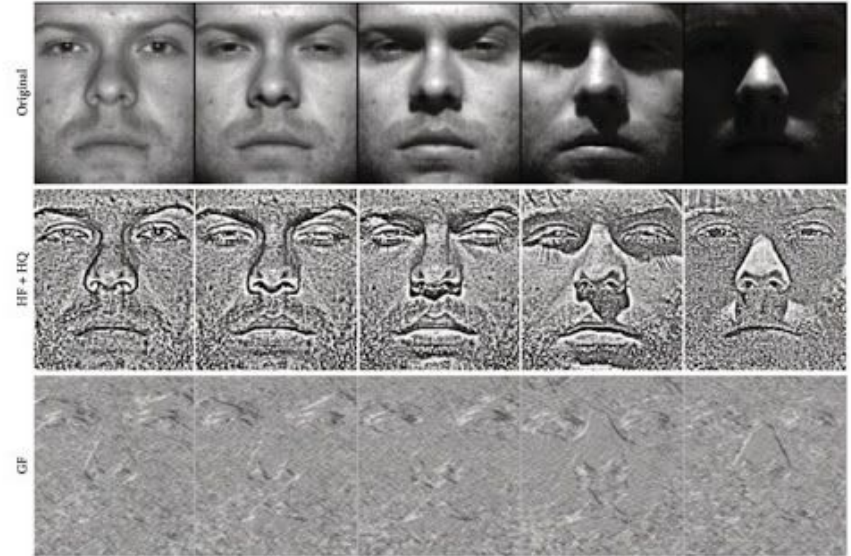


Indirect methods - Adaptive thresholding

b) Feature engineering - Model based algorithm

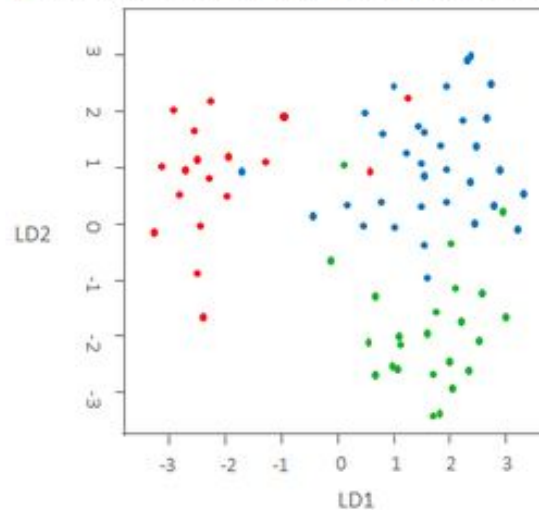
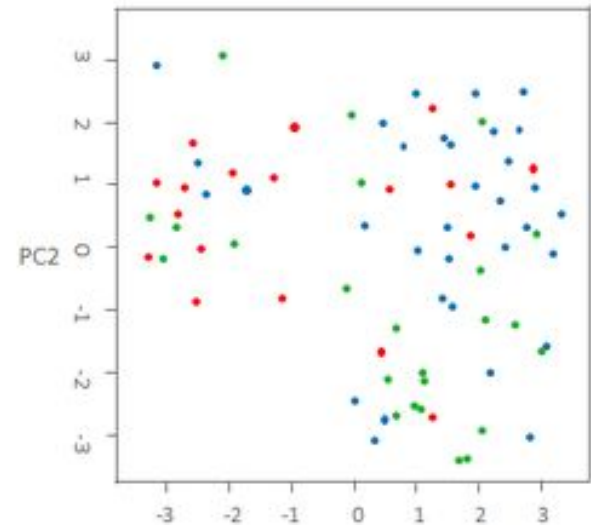
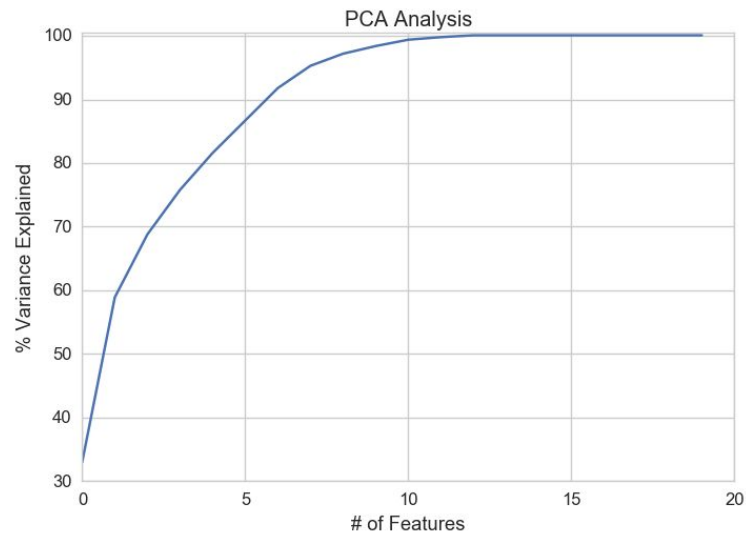


Gabor Filters



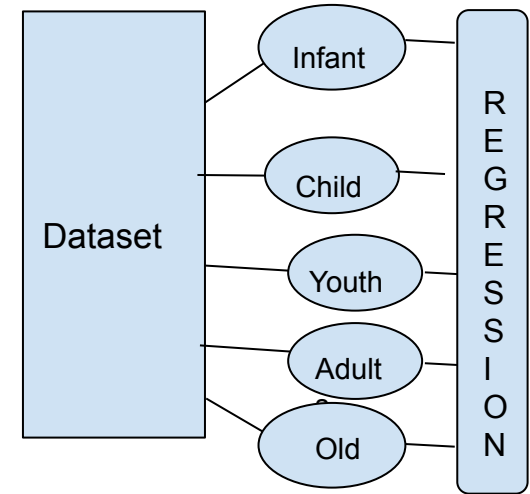
DoG and LoG - SIFT Algorithms

Dimensionality reduction



SVM Model Analysis

- SVM model used 5 fold CV and used these additional accuracy improvements :
 - Voting classifier using Poly and rbf kernel
 - Random Forest(classification) - SVM (regression)
 - Double ensembling for coloured and grey image
- Result - 63.5% test accuracy for voting classifier
- After the hybrid model was used, the final MAE for age group of 15 to 25 was 2.56!



Conclusion

Various Learning outcomes -

- Technical -
 1. Different models and different methods
 2. Importance of open - source and free products and platforms.
 3. Various techniques for real-world applications

- Soft skills gained
 1. Presentations and reports
 2. Documentation and comments
 3. Team project and related platforms

THE WAY **FORWARD**



What's next ?

- Research paper
 - Different methods and their results.
 - Model Benchmarking.
 - Some other interesting ideas.
- Application domain
 - Embedding with IoT and making a real life solution.
 - Smart Cosmetic solutions.
 - Forensics
 - Authentication

End of presentation



Thank You!

A blue A-frame sign stands on a dark blue surface against a light gray background. The sign is tilted slightly to the right. The words "Thank You!" are written in a white, elegant script font on the front panel. A small black pen is tucked into the bottom right corner of the sign. The sign has a 3D effect with a visible shadow on the surface it stands on.