Facial Demographics

PS Instructor: Prof. Aruna Malapati

Mentor: Mrs. Tanisha Bhayani

Group Members:

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



About Project

- At Silver Touch Technologies, the main project (Facial Demographics) is to predict the *gender* and *age* of a person given his/her face image.
- This is accomplished using Machine Learning / Deep Learning Techniques such as CNNs.

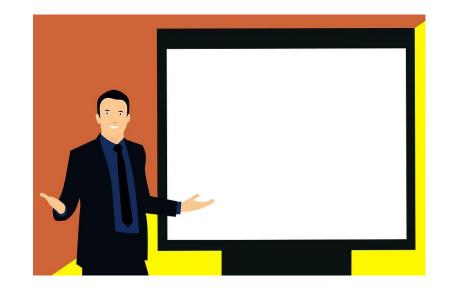
- Different students were asked to work on different approaches –
- 1. **Designing CNN architecture from scratch** Shreyansh, Ashutosh
- 2. Transfer Learning with CNN and ML Models Vikas
- 3. Core ML models such as SVMs Jash

Contents

1. Introduction to Facial demographics

2. Project Outlines

3. Work Plan



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 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: 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.

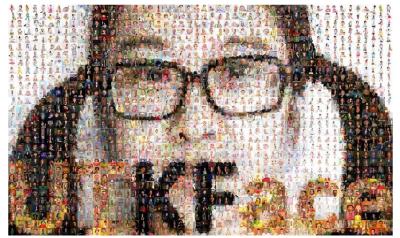
Project Methodology

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:











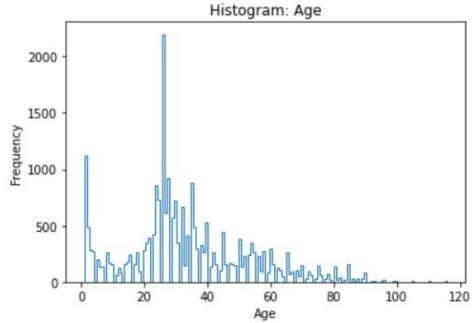
62,308 Images

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: A	Age. dtyne: 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		

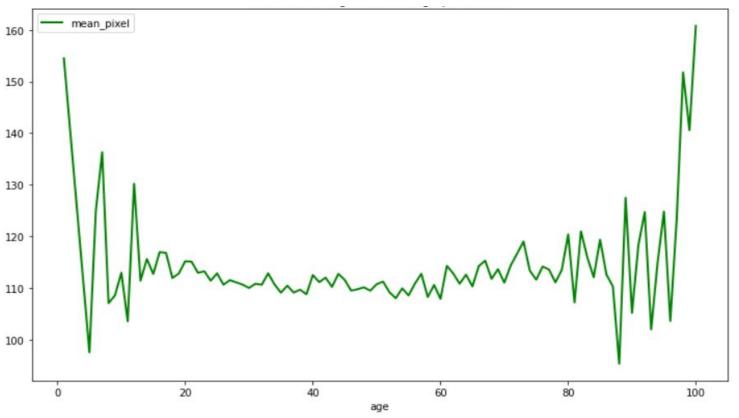
Descriptive Statistics of the dataset for male and female

EDA (Exploratory Data Analysis) of Image data

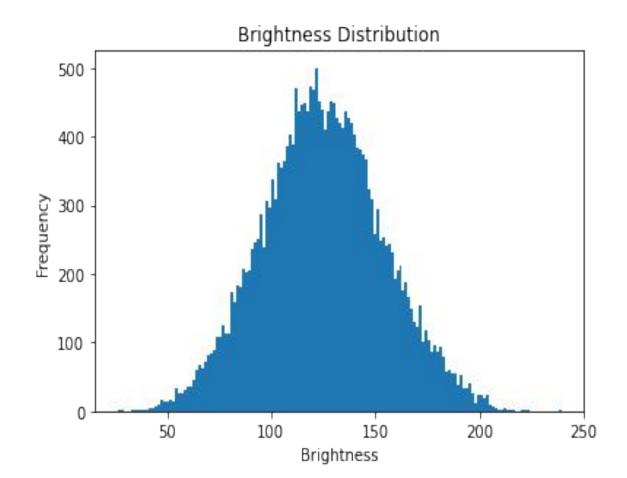
 Earlier EDA was performed on metadata, now we did EDA on the actual image pixel data, as well.



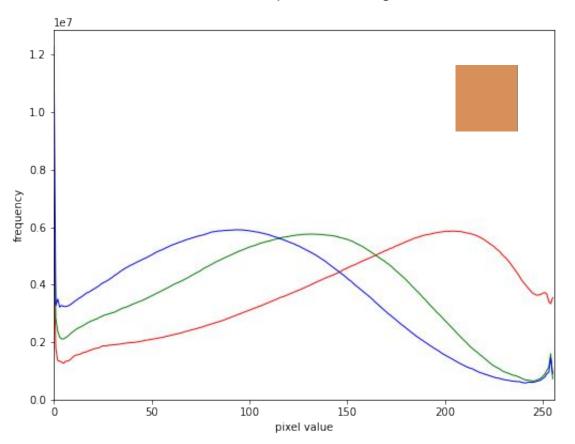
Some examples of the image analysis we did......

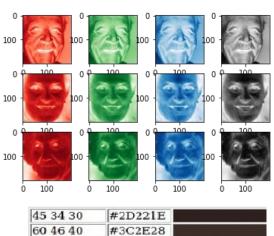


Relation between age and average pixel values



channelwise pixel value histogram





#2D221E	
#3C2E28	
#4B3932	
#5A453C	
#695046	
#785C50	
#87675A	
#967264	
#A57E6E	
#B48A78	
#C39582	
#D2A18C	
#E1AC96	
#F0B8A0	
#FFC3AA	
#FFCEB4	
	#3C2E28 #4B3932 #5A453C #695046 #785C50

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 LearningRateSchedular of keras, with initial Ir of 0.008 & trained the model for 44 epochs.
- Model was trained on 23,708 images.

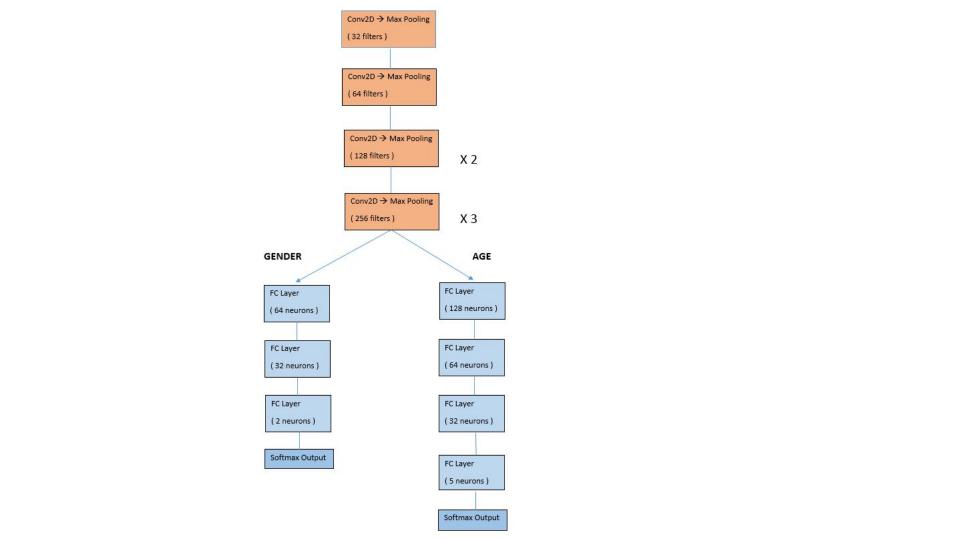
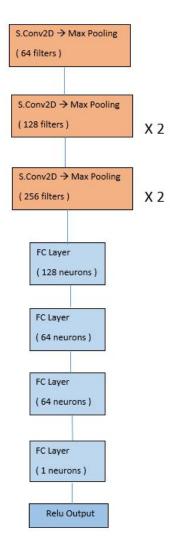


Table: Results for age & gender classifier

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 x 180 x 3
- Loss function *mse* , optimizer *Adam*
- Metrics mae, mse
- LearningRateSchedular was used with an initial Ir of 0.006 that halved Ir 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.



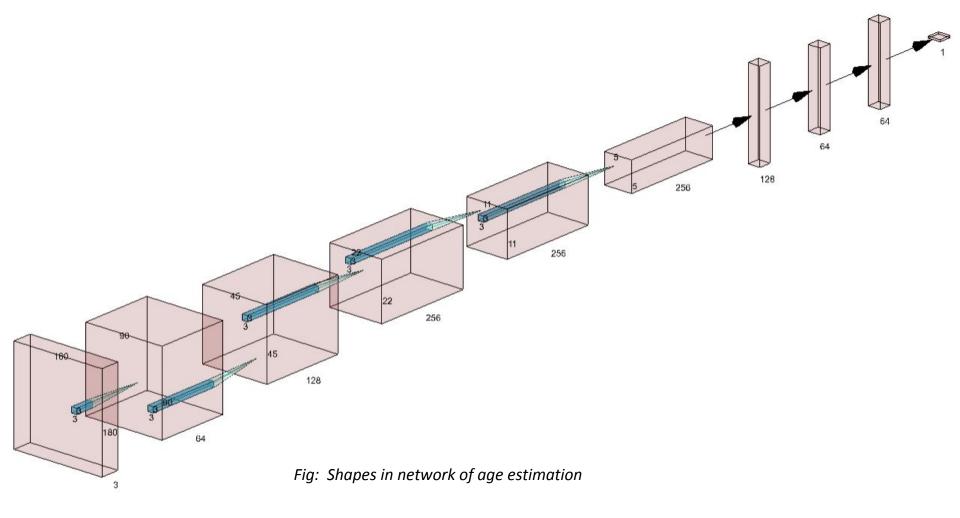


Table: Results for age estimator

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

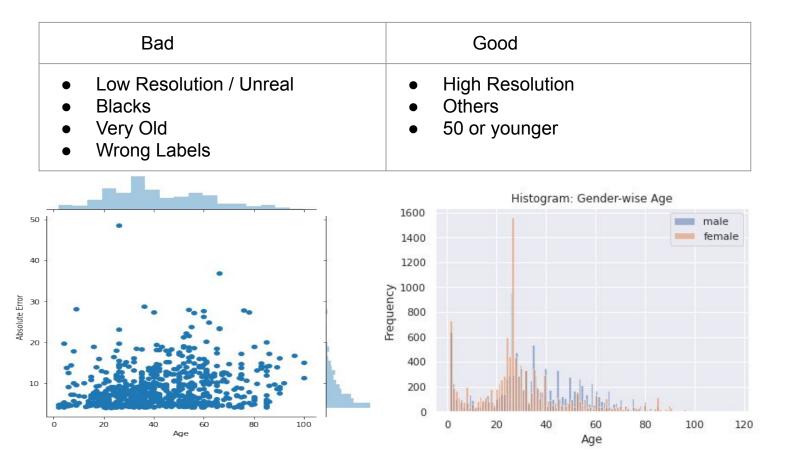
Transfer Learning Update : Age prediction as Regression

VGG16 Features Model Prediction

Model Highlights	Results	Benchmarks
 3 Conv + 3 FC layers SeparableConv2D SpatialDropout BatchNorms Gaussian Noises Weight Constraints Dropout ELU 	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 Ensemble MAE: 4.620075553157043	Various Papers 9.19* 7.36 (Git Repo) 5.44 (MobileNet) 5.39 (CORAL)

^{*} Proceedings of International Joint Conference on Computational Intelligence - Oct-2019

Error Analysis



DL > ML?

- Data and Scalability
- Computation Power
- Challenge Hyperparameter Tuning
- Grid Search vs Random Search

- Data, Assumptions
- Resources
- Problem
- Application
- Time Constraint like this.

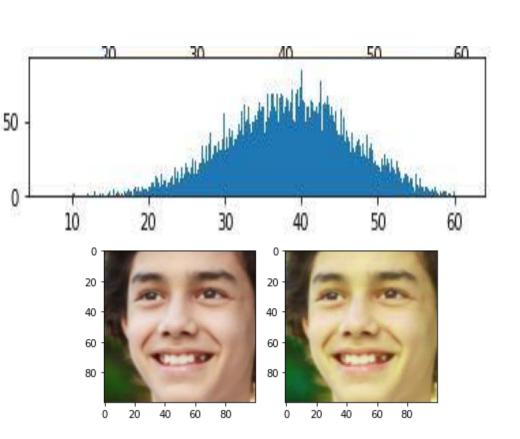
Model	Test
Neural Networks (Regularized)	0.9395
SVC	0.9363538296
LDA	0.9363538296
Voting Classifier - Top3	0.9336569579
QDA	0.9314994606
Stochastic GBoost	0.9309600863
XGBoost	0.9282632147
Bagging	0.9234088457
AdaBoost	0.9234088457
Gradient Boosted Trees	0.9207119741
Random Forest	0.9196332255
LogisticRegression	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

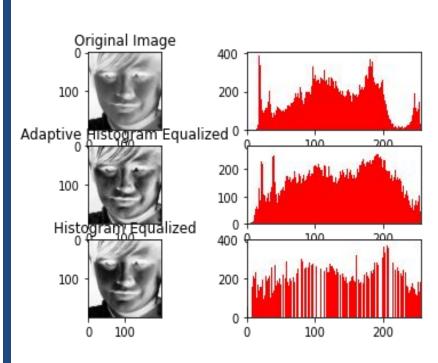
SVM model

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

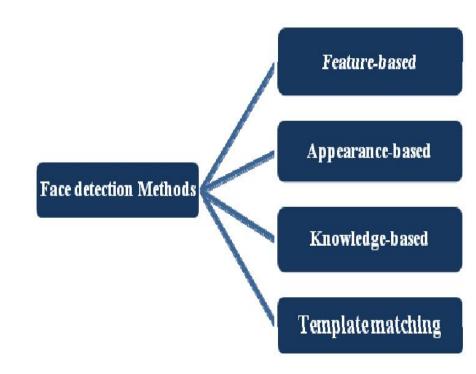
Pre-processing methods



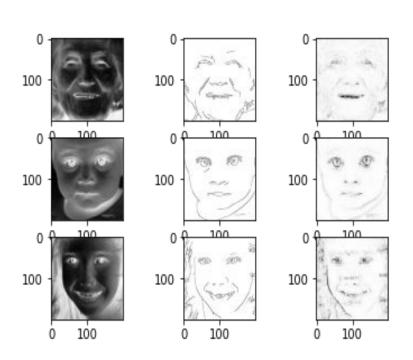


a) Face detection & augmentation

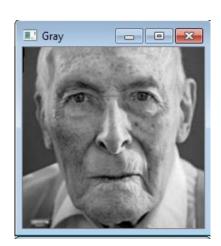
- Viola jones method
 - Haar like features (Feature based)
 - Integral Image
 - Adaboost Cascade (Knowledge based)
- HOG filter was also considered (Template Matching)
- Linear Binary patterns
 (Appearance based)



b) Feature engineering - Model free algorithm



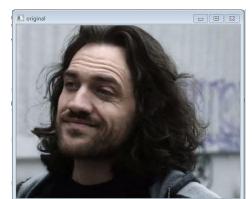
Direct methods - Laplacian and Sobel





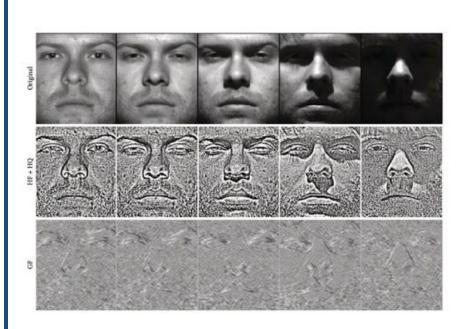
Indirect methods - Adaptive thresholding

b) Feature engineering - Model based algorithm



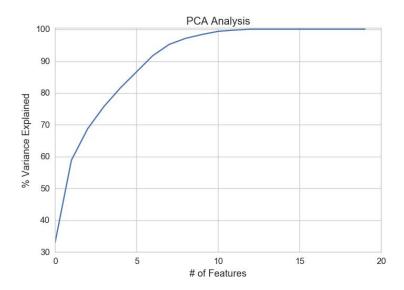


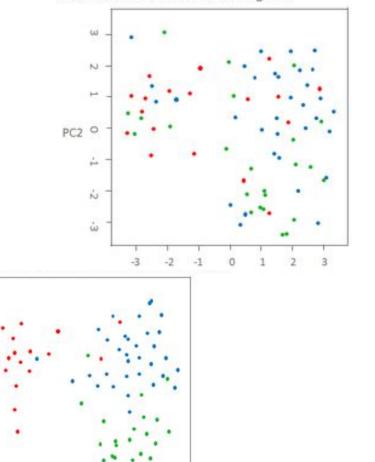




DoG and LoG - SIFT Algorithms

Dimensionality reduction





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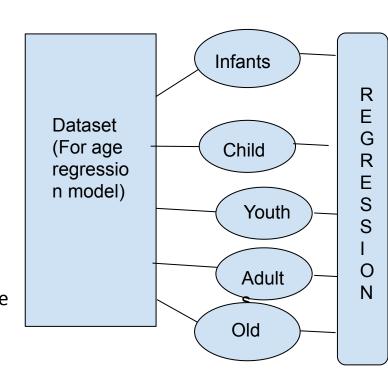
LD1

LD2

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 ensambling for coloured and grey image
- Result 93.5% test accuracy for voting classifier

• After the hybrid model was used, the final MAE for age group of 15 to 25 was 2.56!



THE WAY FORWARD



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
 - Documentation and comments
 - 3. Team project and related platforms

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

