Face position detection using ML algorithms

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Introduction

It is also called facial detection. It is an artificial intelligence (AI) based computer technology used to find and identify human faces in digital images. It now plays an important role as the first step in many key applications including face tracking, face analysis and facial recognition.

Problem Definition

The head pose estimation of the driver is a crucial indicator of driving performance.

Distractions are specially challenging because many times are difficult to predict in advance since they may be due to sudden events in the environment or in the cabin.

Head pose estimation is a challenging problem in itself due to the variability introduced by factors such as driver's identity and expression, cabin and outdoor illumination.

This project is to build a model that predicts the human activities such as looking left, looking right and frontal.

Advantages of Face Detection

- Unlocking Phones
- Law Enforcement
- Airports and Border Control
- Finding Missing Persons
- Banking
- Tracking Students and Attendance

Disadvantage of Face Detection

- Surveillance
- Scope of Error
- Privacy
- Massive Data Strorage

Disadvanatges

Scope of Error

Facial recognition data is not free from error, which could lead to people being implicated for crimes they have not committed.

For example, a slight change in camera angle or a change in appearance, such as a new hairstyle, could lead to error.

In 2018, Newsweek reported that Amazon's facial recognition technology had falsely identified 28 members of the US Congress as people arrested for crimes.

Dataset : DrivFace

What does database contain?

- It is composed of 606 samples.
- We are using extracted features from 640×480 pixel sized images.
- Samples have been collected from 4 Drivers (2 men and 2 women).
- Face bounding box and facial key points (eyes, nose and mouth)

Assigning Image into Classes

1. **Looking Right** : head angles between -45º and -30º.
2. **Frontal** : head angles between -15º and 15º.
3. **Looking Left** : head angles between 30º and 45º.

Format of Image Name

- YearMonthDay_subject_Driv_imNum_HeadPose.jpg
- 20130529_01_Driv_011_f .jpg
- Year-Month-Day : 2013-05-29
- 1st driver
- 11 sequence's image
- Head pose is frontal.

- Range of subject = [1:4]
  - Because of 4 drivers
- Range of imNum = [001:...]
  - Upperlimit not set
- HeadPose :
  - lr (looking-right)
  - f (frontal)
  - lf (looking-left).

Image as table format

- fileName : imagen's name into DrivImages.zip
- subject = [1:4] (contains 4 drivers)
- imgNum = int (no decimal value)
- label : [1/2/3] (works as [lr / f / lf])
- ang : [(-45), (-30) / (-15) 0 15 / 30 15]
- face position : [xF yF wF hF]
- right eye position : [xRE yRE]
- left eye position: [xLE yL]
- Nose position : [xN yN]
- right corner of mouth : [xRM yRM]
- left corner of mouth : [xLM yLM]

Literature Survey :

Year	Research Paper	Methods	Accuracy	Author
2016	A reduced feature set for driver head pose estimation (Given with project link)	Linear Regression Subspace based Methods	81 %	Katerine Diaz-Chito , Aura Hernández-Sabate, Antonio M. López
2020	Particle swarm optimization based block feature selection in face recognition system	Particle Swarm Optimization (PSO) Feature Selection	93.5 %	Nour Elhouda Chalabi Abdelouahab Attia Abderraouf Bouziane Zahid Akhtar
2020	Face recognition framework based on effective computing and adversarial neural network and its implementation in machine vision for social robots	Counter Neural Network Deep Learning	98.46 %	Chenglin Yu Hailong Pei

Literature Survey :

A reduced feature set for driver head pose estimation

Link : https://www.sciencedirect.com/science/article/abs/pii/S1568494616301752?via%3Dihub

This paper proposes a new automatic method for coarse and fine head's yaw angle estimation of the driver. We rely on a set of geometric features computed from just three representative facial key points, namely the center of the eyes and the nose tip.
Regression methods apply a regression model on a training set
in one or more directions (angles).

Conclusion :
A new methodology for driver coarse and fine head's yaw angle estimation by using a feature set generated from a reduced set of facial key points. The approach is based on a combination of subspace methods, as PCA and FLD, and multiple linear regression. we can conclude that 3 facial key points, corresponding to the center of both eyes and the nose tip, are enough to extract 10 geometric features based on angles and Euclidean distances and obtain accurate and precise results for both coarse and fine head pose estimation.

Literature Survey :

Face recognition framework based on effective computing and adversarial neural network and its implementation in machine vision for social robots

Link : https://www.sciencedirect.com/science/article/abs/pii/S0045790621001324

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Literature Survey :

Particle swarm optimization based block feature selection in face recognition system

Link : https://link.springer.com/article/10.1007%2Fs11042-021-11367-0

Most face recognition systems employ feature selection after feature extraction to enhance the accuracy of the frameworks. In other words, feature selection is one of the important phases that any recognition system must go through as the final results depend on it. Moreover, face also contains other characteristics such as gender, age, ethnicity and emotions, known as soft biometrics. In order to examine the impact of optimization in feature selection and thereby in face recognition, our work can be broadly divided into two steps. The first step is a block division of the images and feature extraction using the BSIF descriptor. The second step is applying the PSO to reduce the size of features by chosen blocks and to improve the accuracy.

Conclusion :
A PSO based bock wise feature selection in face recognition has been presented. In the proposed face recognition system, a block division technique is applied to the capture face sample to divide the images into a regular number of sub blocks. In order to ensure the extraction of all the distinctive features from the whole image, PSO technique is used to select block features .

Methodology

We are using following traditional machine learning models to predict different Face position :

1. Logistic Regression
2. Single Layer Perceptron (one architecture)
3. Sigmoid Neuron (one architecture)
4. Multi-Layer Perceptron (one input layer, one hidden layer, one output layer)

Result Analysis

Logistic Regression

- Overall Accuracy (training data): 95.24 %
- Overall Accuracy (test data): 92.62%
- Class-wise Accuracy :
  1) 0.625 2) 0.987 3) 0.626
- Precision : 89.4%
- Recall : 74.2 %
- F1- score : 78.2 %

Result Analysis

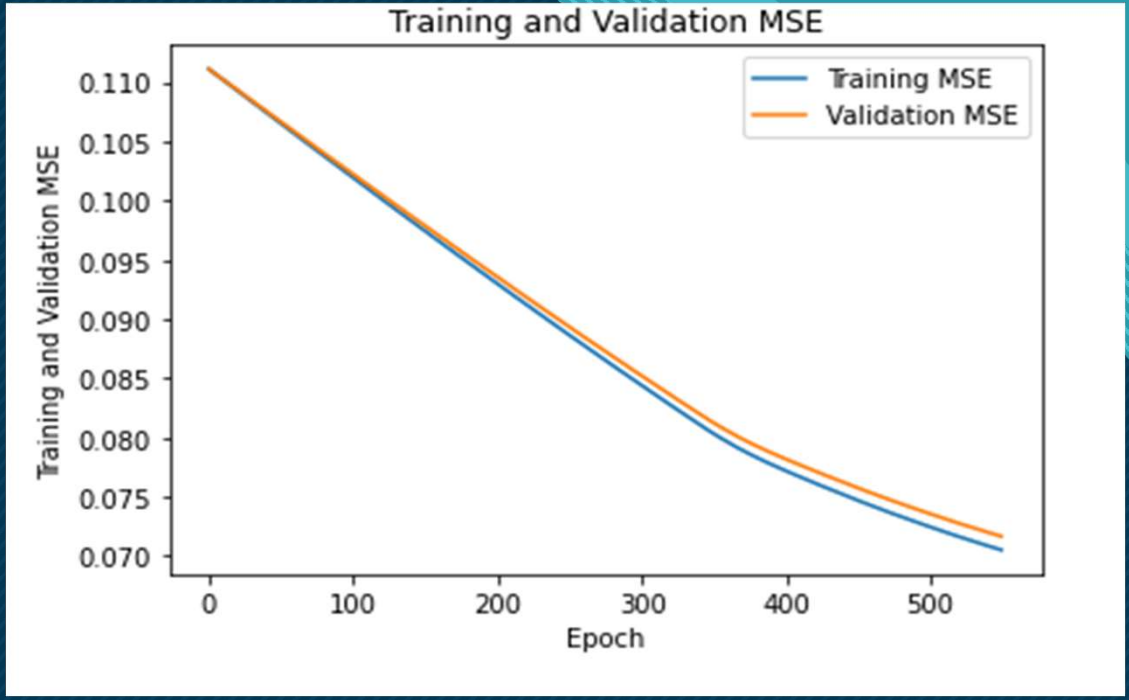
Single Layer Perceptron

- **Overall Accuracy (training data): 91.99 %**
- **Overall Accuracy (test data): 91.57 %**
- **Class-wise Accuracy :**
  1) 0 **2)** 0.985334 **3)** 0.544048
- **Precision : 55.8 %**
- **Recall : 50.6 %**
- **F1- score : 51.6 %**

Result Analysis

Is there any over-fitting issue during training in Single Layer Perceptron model ?

To detect the overfitting issue we have taken validation set. As we can see from Figure, that training mse and validation mse both are decreasing epoch by epoch so our SLP model is not getting overfit during training. We got 90.956% accuracy on training dataset, 89.691% on validation set and 87.705% on testing set.



Result Analysis

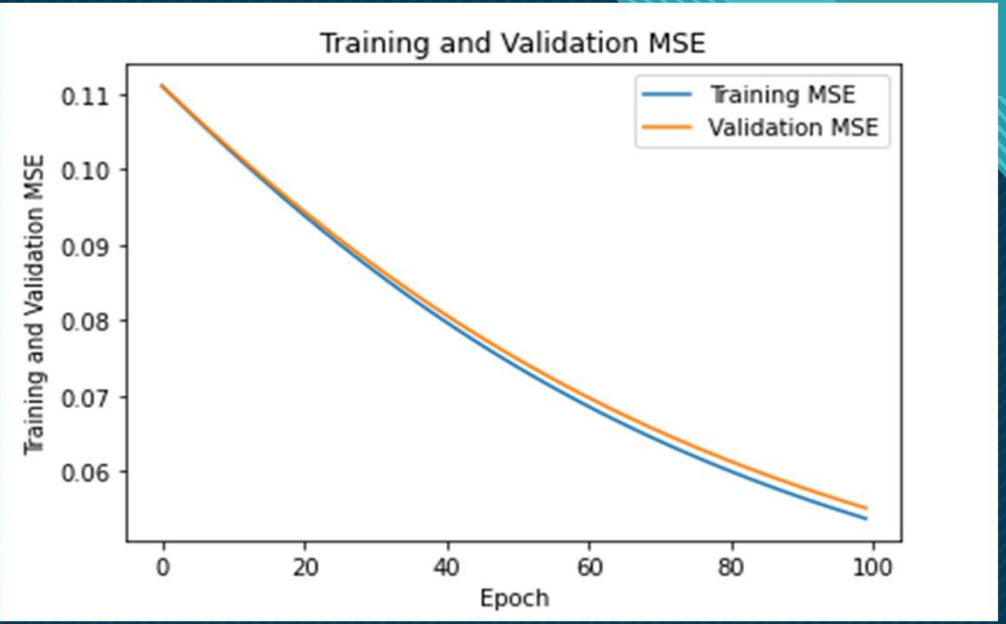
Sigmoid Neuron

- Overall Accuracy (training data): 90.09 %
- Overall Accuracy (test data): 90.09%
- Class-wise Accuracy :
  1) 0 2) 1 3) 0
- Precision : 29.8 %
- Recall : 33 %
- F1- score : 31.6 %

Result Analysis

Is there any over-fitting issue during training in Sigmoid Neuron model ?

To detect the overfitting issue we have taken validation set. As we can see from Figure, that training mse and validation mse both are decreasing epoch by epoch so our SLP model is not getting overfit during training. We got 90.956 % accuracy on training dataset, 89.690 % on validation set and 87.704 % on testing set.



Result Analysis

Multi Layer Perceptron

- Overall Accuracy (training data): 90.094 %
- Overall Accuracy (test data): 90.096%
- Class-wise Accuracy :
  1) 0 2) 1 3) 0
- Precision : 29.6%
- Recall : 33 %
- F1- score : 31.2 %
- Weighted Average : [80.6 % , 89.4 % , 84.8 %]


THANK YOU