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EMPIRICAL REVIEW ON FACE RECOGNITION MODELS

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ABSTRACT

Face (expression) recognition (FR) is a very exciting problem in the area of image processing and computer vision. Any FR system should be savvy to unequivocally detect facial images. Several kinds of features have been considered for face (expression) recognition in past years. It is noticed that some of the simple aggregate statistical features have not attracted the researchers for face (expression) recognition problems. In this paper, our contribution is about feature ordering and discussing the ability of distinguishing and non-distinguishing images. This article explores the ability of representing and classifying facial images through some aggregate statistical features such as mean, standard deviation (Std), Coefficient of Variation (Cv), and 7 invariant (spatial) moments.

KEYWORDS: *ANOVA, Mean, STD, CV, IM, Post-Hoc Analysis, Invariant (Spatial) Moments*

INTRODUCTION

The interest in the face (expression) recognition has been growing greatly during the past two decades due to the need for more secure ways of protecting information for both corporate and federal interests, and many more. With the invention of Digital Camera Technology and Internet Photo Sharing sites, the biometric facial recognition technology is now utilized in everything right from surveillance to targeted marketing. Today, many industries are getting assistance with facial recognition system. Like in taking logs, the official record of events, computer entertainment, virtual reality, multimedia, database retrieval, information security for example. operating system, medical records, online banking., automated border controls, personal security driver monitoring system, Forensic applications, passport, driver's license, the desire to development of human-computer interface (expression)s, interactive movies and games, home video surveillance system.

Computer and telephone companies are providing more layers of biometric security to customers, Law enforcement agencies using face (expression) recognition system to keep the public safer, in the investigation, in identity verification for example, in the year 2011, using facial recognition system confirmed the identity of Osama Bin Laden after he was killed in the USA. theraid, Airports, and metro station authorities improving travelers' security and convenience, big commercial companies have used facial recognition technology to draw attention and promote their sales. For example, in the year 2009, Coca-Cola Zero launched a Facial Profiler App on Face (expression)book that scanned photos for people who looked like you. In the year 2012 Suhas et al (2012) developed a face (expression) recognition system using Principal

Component Analysis and Linear Discriminant Analysis.

Automatic facial detection and recognition system is an active research area bridging other disciplines like machine learning, image processing, pattern recognition, artificial intelligence, biometrics and computer vision. This is represented in the Figure 1. Face (expression) recognition system is a necessary first step in many applications such as human computer interface (expression), facial expression recognition, and gender recognition [6].

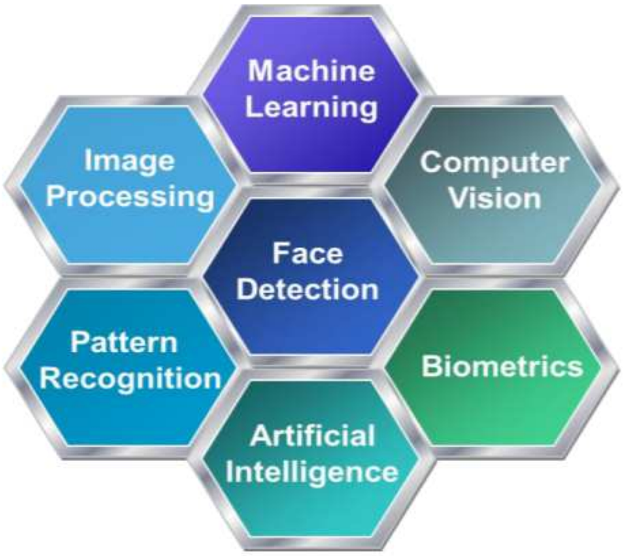


Figure 1: Interconnection of Face (Expression) Recognition and Other Fields of Study.

LITERATURE REVIEW

In the late 19th century, Alphonse Bertillon, a police official in Paris, developed a manual database by storing photos of the suspect's full face (expression), profile with name, bodily measurements, and other information. He tried to identify criminals with accurate measurements. He also published guidelines to measure body parts and classified information. This was soon adopted by police worldwide. Later, the law enforcement started using photographs of wanted conspirators onto posters. In cases, where no photo of the suspect was available, the police were dependent on hand-drawing of a suspect's face (expression) Leone (2021).

In 1960, Woodrow Wilson Bledsoe, a pioneer of artificial intelligence introduced semi-automated computer-based facial recognition. He devised a system for manually noting key facial benchmarks on each image like the width of the mouth, the distance between eyes, nose etc. These metrics were inserted into a database. Then, when a new face (expression) photograph of an individual was given, the Bledsoe's system was able to retrieve the face (expression) from the database that most closely matched.

In the 1970s, the researchers Goldstein, Harmon, and Lesk were able to add increased accuracy of manual facial recognition system by including 21 specific key facial landmarks like lip thickness and hair color in order to identify face (expression)s automatically. The Kanade feature-based recognition system developed in1973 is one of the first automated face (expression) recognition systems. A work by Kelly (1970) on visual identification of people by computer related to automatic face (expression) recognition was also carried out at Stanford University.

In 1980s and 1990s researchers continued working in the field of Biometrics. In 1988, the research by mathematicians Kirby and Sirovich (1990) at Brown University applied linear algebra to facial recognition called Eigen face (expression)s. They were able to show that feature analysis on a collection of facial images could form a set of basic features. They were able to prove that less than one hundred values were required in order to accurately code a normalized face (expression) image. In 1991, computer scientists Matthew Turk and Pentland (1991) at MIT expanded upon the Eigen face (expression)s approach by discovering how to detect face (expression)s within images using technology and environmental factors leading to the automatic facial recognition system.

From 1993 to 2000 the Defense Advanced Research Projects Agency (DARPA) and the National Institute of Standards and Technology (NIST) created a database of facial images. In 2003 the database was updated to include high-resolution images. In 2014 the FBI under state-of-the-art facial recognition technology replaced its old fingerprinting system with the world's biggest biometric database including voice features, palm prints, and even DNA profiles by combing civil and criminal information within one master database. It allowed them to compare the suspect information with a large database of facial images collected from digital camera devices seized under a search warrant, employment background checks, surveillance cameras, mug shots, etc. to find a correct match. The facial recognition system setup consists of advanced cameras that capture photos of people who pose or simply walk by, and sophisticated software working on those pictures will attempt to find the right match from this gigantic database to identify the person(s) in the image. The interest in the face (expression) recognition has been growing greatly during the past two decades due to the need for more secure ways of protecting information for both corporate and federal interests and many more.

PROPOSED MODEL

A randomly selected sample of 10 people images from BioIDFace (expression) Database with labels as given in Figure 2. The following section 1 gives the descriptive statistics of features and identifying the significant features using ANOVA. The number of treatments can be as many as distinct persons in the image pool. The extracted feature data can be viewed as multivariate data with several treatments.

In section 2 the conditional distribution of features/ ordering statistically significant features has been computed and hence an attempt form rule for distinguishing classes. A hierarchical clustering analysis has been carried out in section 3with Post-hoc analysis on each of the features and conclusions discussed.

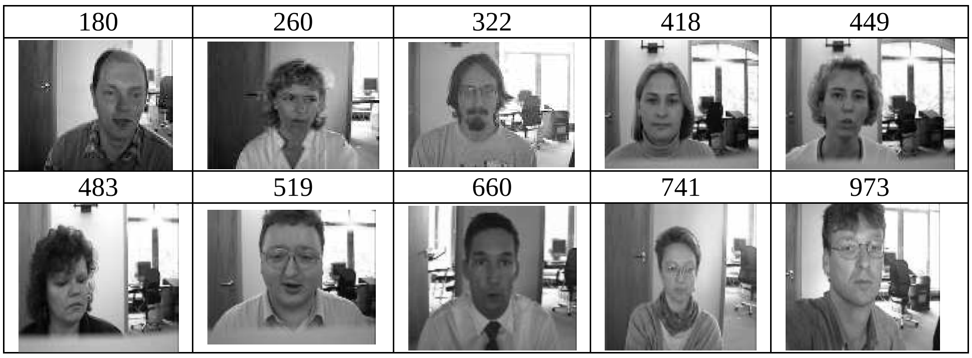


Figure 2: Sample Face (Expression)s of Selected 10 Individuals.

Descriptive Statistics and ANOVA

Ten features such as mean, standard deviation, coefficient of variation (Cv) and seven invariant moments IM1, IM2, IM3, IM4, IM5, IM6, IM7 descriptive statistics were extracted from test sample of10images. An analysis of variance was carried out on all extracted features by treating image labels as treatments and their feature values as responses to see which of these features is significant.

A detailed descriptive statistical analysis was carried out on this multivariate sample. A sample of descriptive statistics on 4 features is shown in Table 1.

Table 1: Descriptive Statistics Sample of Mean, Std, CV, and IM1

Descriptive Statistics					
		Mean	**Std**	**CV**	**IM1**
N	Valid	445	445	445	445
	Missing	0	0	0	0
Mean:		127.3593933320	66.2959908950	52.6754208830	.00136060037
Std. Error of Mean:		.69235505205	.31009820263	.36009793650	.000007739106
Median:		132.3478839000	66.4615373300	52.7363983200	.00132788600
Mode:		88.52934696[a]	55.50284044[a]	38.97597043[a]	.001135418[a]
Std. Deviation:		14.60524582308	6.54152875075	7.59627429217	.000163256624
Skewness:		-.590	.241	1.213	1.362
Std. Error of Skewness:		.116	.116	.116	.116
Kurtosis:		-.593	-.307	4.427	1.671
Std. Error of Kurtosis:		.231	.231	.231	.231
Percentiles:	10	106.8903645800	56.5492450660	42.9136372860	.00118799580
	20	109.3317617600	60.3117317900	47.2380004020	.00123061540
	25	113.6493162000	61.4752254600	47.6135338250	.00123663550
	30	122.7412114200	62.8173917200	48.5140544940	.00126492640
	40	125.3919398600	64.5046143920	49.9919658780	.00130659320
	50	132.3478839000	66.4615373300	52.7363983200	.00132788600
	60	133.5286713000	68.4346086340	54.8456347160	.00135116780
	70	136.9330073200	69.4104961080	55.6545403880	.00138998880
	75	138.6403109000	70.1546588800	56.3233889750	.00141607000
	80	140.2538880400	71.5579484180	57.4823551700	.00143902980
	90	142.6135744400	74.8565230460	61.6476134700	.00159126880

An analysis of variance is performed on feature by feature and the results are provided in Table 2 and then followed by their feature distribution Histograms.

Table 2: Analysis of Variance of Each of the Feature

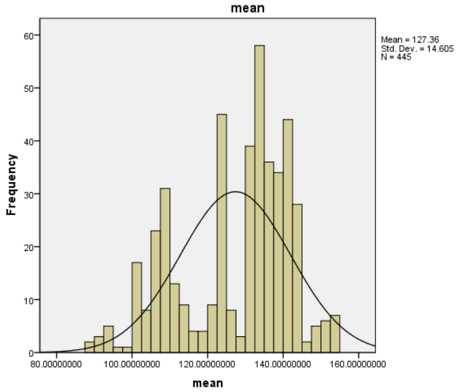
ANOVA						
		Sum of Squares:	**Degrees of freedom:**	**Mean Square:**	**F:**	**Significance:**
Mean:	between groups→	46366.135	9	5151.793	46.355	.000
	within groups→	48344.929	435	111.138		
	total→	94711.063	444			
Std:	between groups→	14433.191	9	1603.688	152.773	.000
	within groups→	4566.279	435	10.497		
	total→	18999.470	444			
Cv:	between groups→	10957.020	9	1217.447	36.117	.000
	within groups→	14663.282	435	33.709		
	total→	25620.302	444			

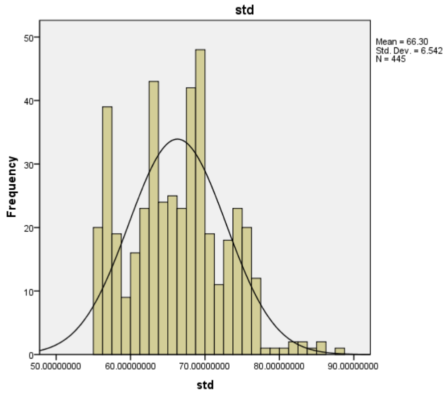
Table 2: Contd.,

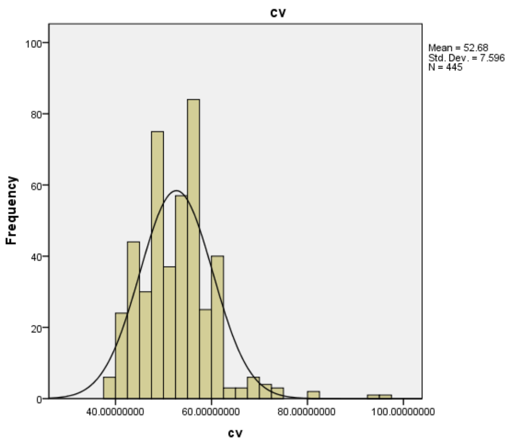
IM1:	between groups→	.000	9	.000	48.996	.000
	within groups→	.000	435	.000		
	total→	.000	444			
IM2:	between groups→	.000	9	.000	120.491	.000
	within groups→	.000	435	.000		
	total→	.000	444			
IM3:	between groups→	.000	9	.000	7.276	.000
	within groups→	.000	435	.000		
	total→	.000	444			
IM4:	between groups→	.000	9	.000	20.291	.000
	within groups→	.000	435	.000		
	total→	.000	444			
IM5:	between groups→	.000	9	.000	3.060	.001
	within groups→	.000	435	.000		
	total→	.000	444			
IM6:	between groups→	.000	9	.000	21.143	.000
	within groups→	.000	435	.000		
	total→	.000	444			
IM7:	between groups→	.000	9	.000	4.715	.000
	within groups→	.000	435	.000		
	total→	.000	444			

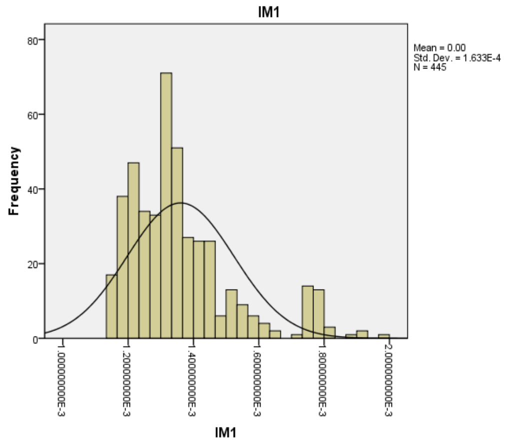
A univariate one-way analysis of variance on the sample image classes for each of the feature in Table 2 shows that the F-statistic is higher and their p value smaller than 0.05 or 0.01. We conclude that the considered features mean, Std, Cv, and the seven Invariant Moments (IM1, IM2….IM7) are significant and they contribute or consist information about the distinguishing facial image classes.

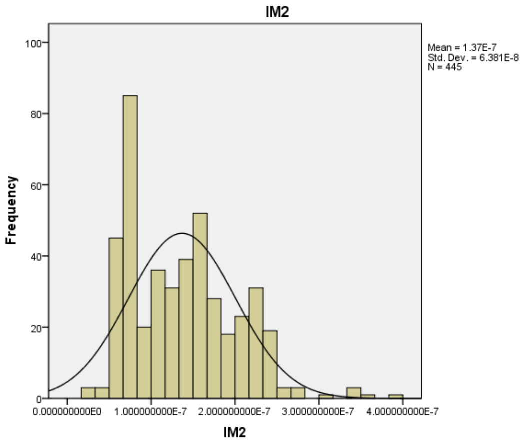
The histograms of features are displayed in the following Figure: 3.We see no outliers. All features are roughly normally distributed. The distribution of IM3 and IM4 data is nothing like a normal distribution.

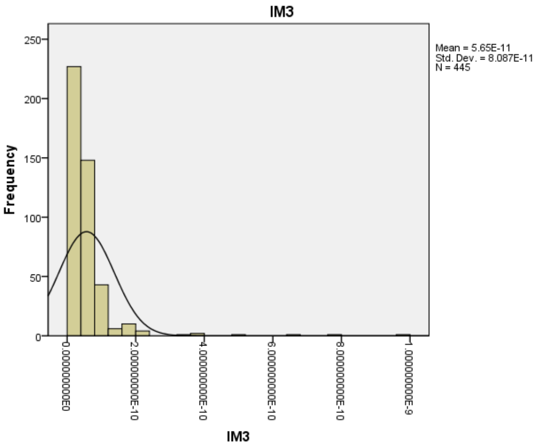


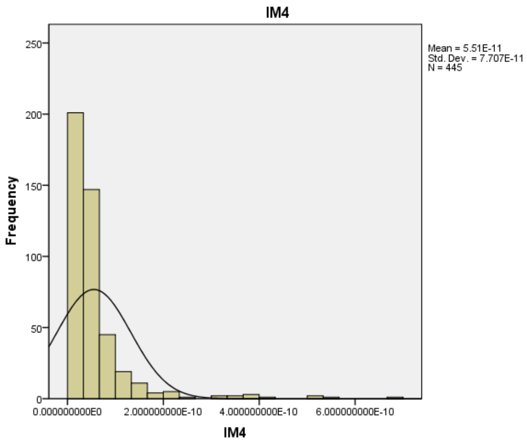


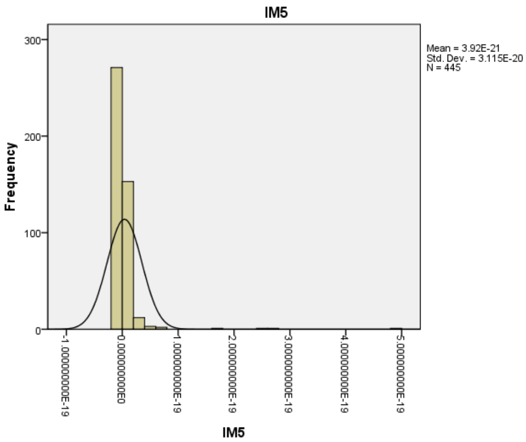

cv
Mean = 52.68
Std. Dev. = 7.596
N = 445
Frequency
cv


IM1
Mean = 0.00
Std. Dev. = 1.633E-4
N = 445
Frequency
IM1


IM2
Mean = 1.37E-7
Std. Dev. = 6.381E-8
N = 445
Frequency
IM2


IM3
Mean = 5.65E-11
Std. Dev. = 8.087E-11
N = 445
Frequency
IM3


IM4
Mean = 5.51E-11
Std. Dev. = 7.707E-11
N = 445
Frequency
IM4


IM5
Mean = 3.92E-21
Std. Dev. = 3.115E-20
N = 445
Frequency
IM5

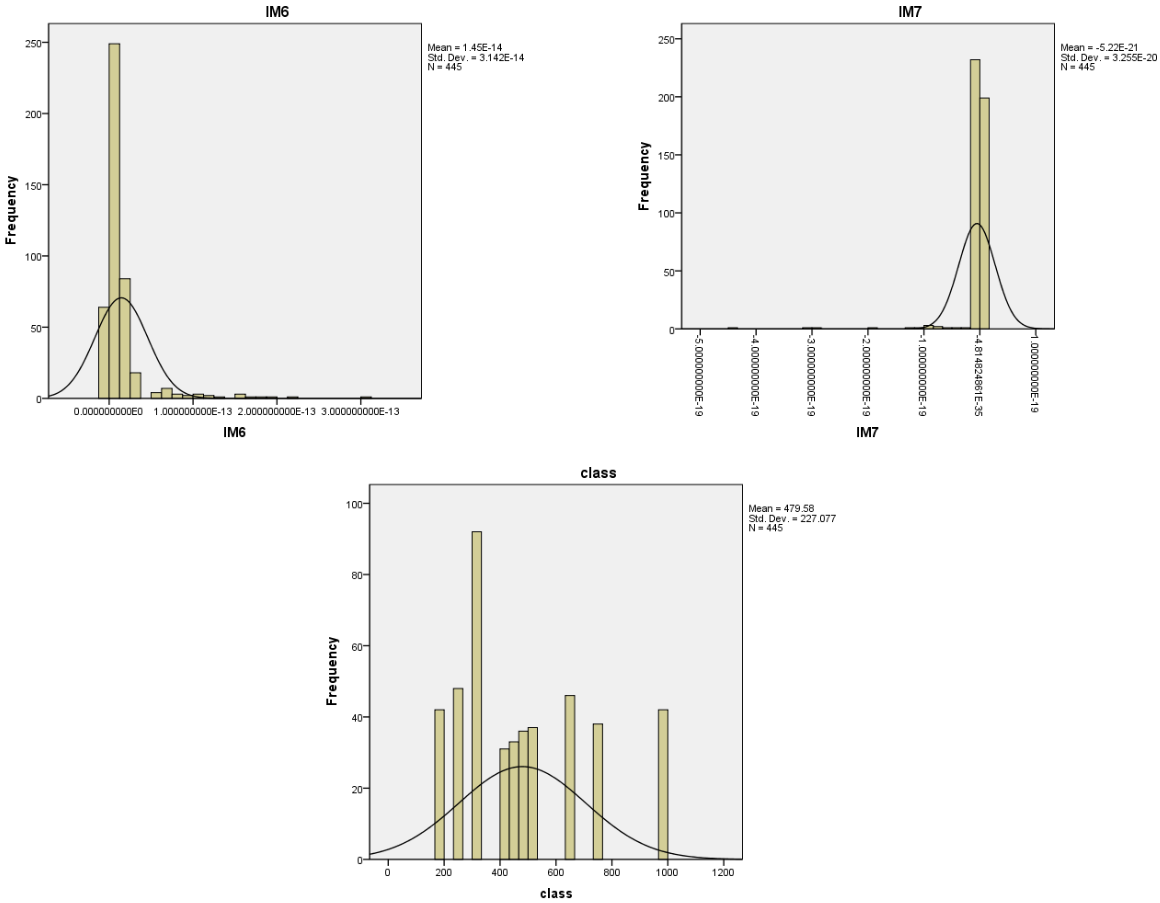


Figure 3: Histograms of Features.

ORDERING OF FEATURES

The significant features recognised from ANOVA table are arranged in the decreasing value of F statistic. This is the feature ordering. The features are now ranked as given in table 3. Hence, we assume that these features are potential enough to distinguishing and non-distinguishing image classes.

Table 3: Ranked Features

Feature name	F-statistic from ANOVA	Ranks
Std	152.773	1
IM2	120.491	2
IM1	48.996	3
mean	46.355	4
Cv	36.117	5
IM6	21.143	6
IM4	20.291	7
IM3	7.276	8
IM7	4.715	9
IM5	3.06	10

The feature with highest F value will be routing into the Image classes distinguishing model first, then the second feature with the next highest F value, and so on.

POST-HOC ANALYSIS

Post hoc tests are an integral part of Analysis of Variance (ANOVA) and useful to analyze the results of the experimental data. Since all the selected features are significant among 10 image classes, a post-hoc analysis is carried on eachfeature data to see which pair of image classes differ significantly under each feature. A post-hoc analysis is carried out on each feature. A sample of post-hoc pair wise statistics analysis for the top ranked significant feature variable “std” on the image class 180 with each of other classes is given in table 4 below.

Table 4: Post-HOC Test Results on Feature” Std”

Dependent Variable:	(I) Class:	(J) Class:	Mean Difference (I-J):	Std. Error:	Sig:	95% Confidence Interval:	
						Lower Bound:	Upper Bound:
Std	180	260	5.60412497738*	0.684562	0	4.258665	6.949585
		322	-3.33141414987*	0.603352	0	-4.51726	-2.14557
		418	-3.11159204208*	0.767172	0	-4.61942	-1.60377
		449	-3.29872666656*	0.753678	0	-4.78003	-1.81742
		483	-10.24388442845*	0.735882	0	-11.6902	-8.79756
		519	3.64732255810*	0.730507	0	2.21156	5.083086
		660	8.00676296579*	0.691472	0	6.647722	9.365804
		741	10.05779259221*	0.725379	0	8.632109	11.48348
		973	-2.43322305262*	0.707012	0.001	-3.82281	-1.04364

We noticed that the “std” has successfully distinguished the class 180 from all other classes. The labelled class 180 is significantly differing with 260,322,418, 449, 483, 519, 660, 741 and 973classes. Thus the feature “std” will contribute information about the image distinguishing and can be the part of the model of face (expression) recognition.

Another sample of post-hoc test on the significant dependent variable “mean” discussed below. The class of 180 with all other classes is given in table 5 below.

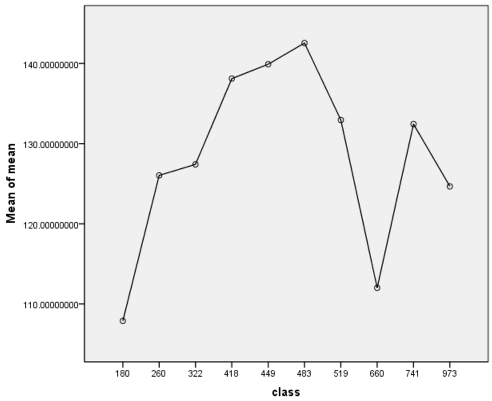
Table 5: Post-HOC Test Results on Feature” Mean”

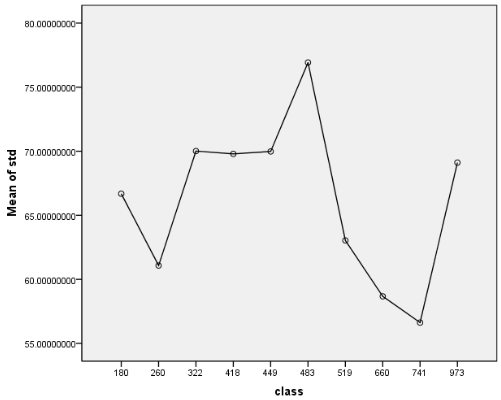
Dependent Variable:	(I) Class:	(J) Class:	Mean Difference (I-J):	Std. Error	Sig:	95% Confidence Interval:	
						Lower Bound:	Upper Bound:
Mean:	180	260	-18.15018680446*	2.227444	0	-22.5281	-13.7722958
		322	-19.52397918021*	1.963201	0	-23.3825	-15.6654411
		418	-30.22499182496*	2.496242	0	-35.1312	-25.3187959
		449	-32.01614348723*	2.452335	0	-36.836	-27.1962442
		483	-34.65693781071*	2.394431	0	-39.363	-29.9508464
		519	-25.05634818346*	2.376944	0	-29.7281	-20.3846262
		660	-4.1201	2.249928	0.068	-8.54218	0.301983838
		741	-24.54972619712*	2.360257	0	-29.1887	-19.9107996
		973	-16.78028503095*	2.300494	0	-21.3018	-12.2588187

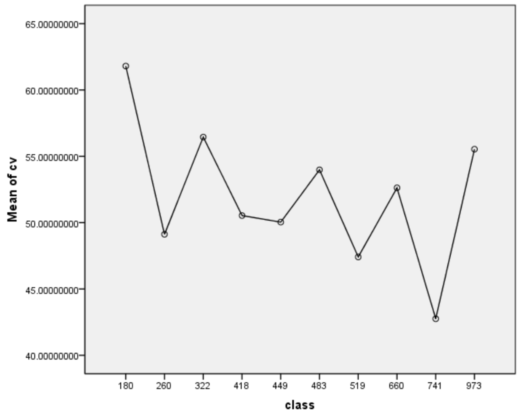
As we noticed the individual labeled 180, is significantly differing with all other labeled classes except 660. In other words, the feature “mean” is able to distinguish the class 180 from 260, 322, 418, 449, 483, 519, 741, and 973. The images 180 and 660 have the same mean. Therefore, it means there will be some classes with equal mean among the image classes. Thus this feature may not contribute clear information in distinguishing image classes even though is proved to be a significant feature in ANOVA. This feature may be considered in building the model. There is a need to probe further in this direction.

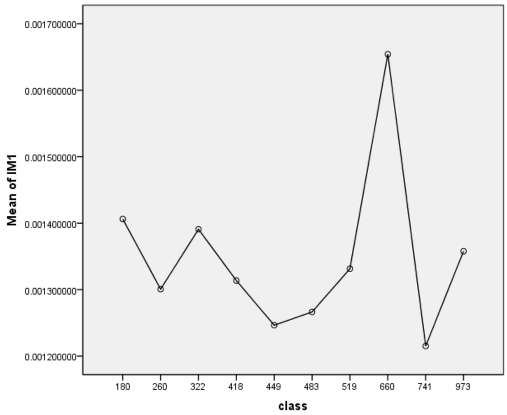
MEAN PLOTTING

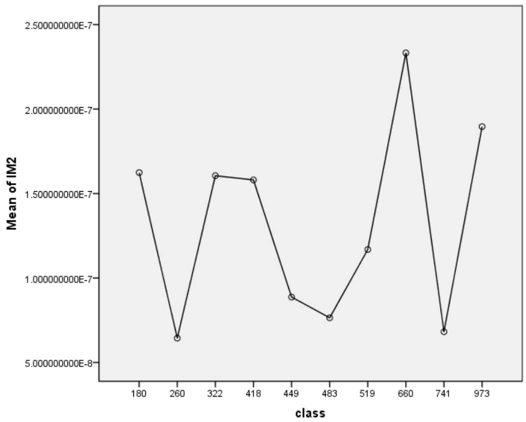
A visual display of the feature means plots help us to visualize our results and therefore included them in our write up. We can see increases and decreases in mean values of each feature. For example, in first mean plot of data it shows that label 519 and 741 are not clearly distinguishable with respect to mean of means.

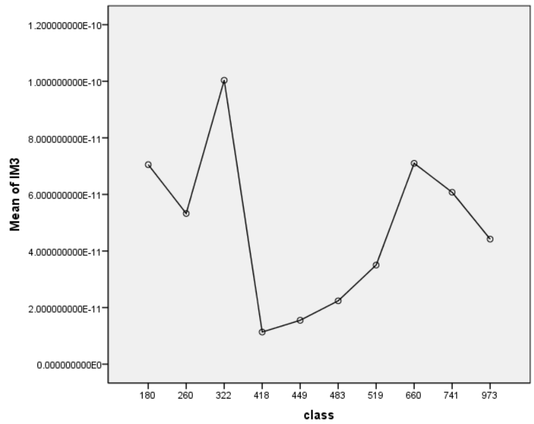












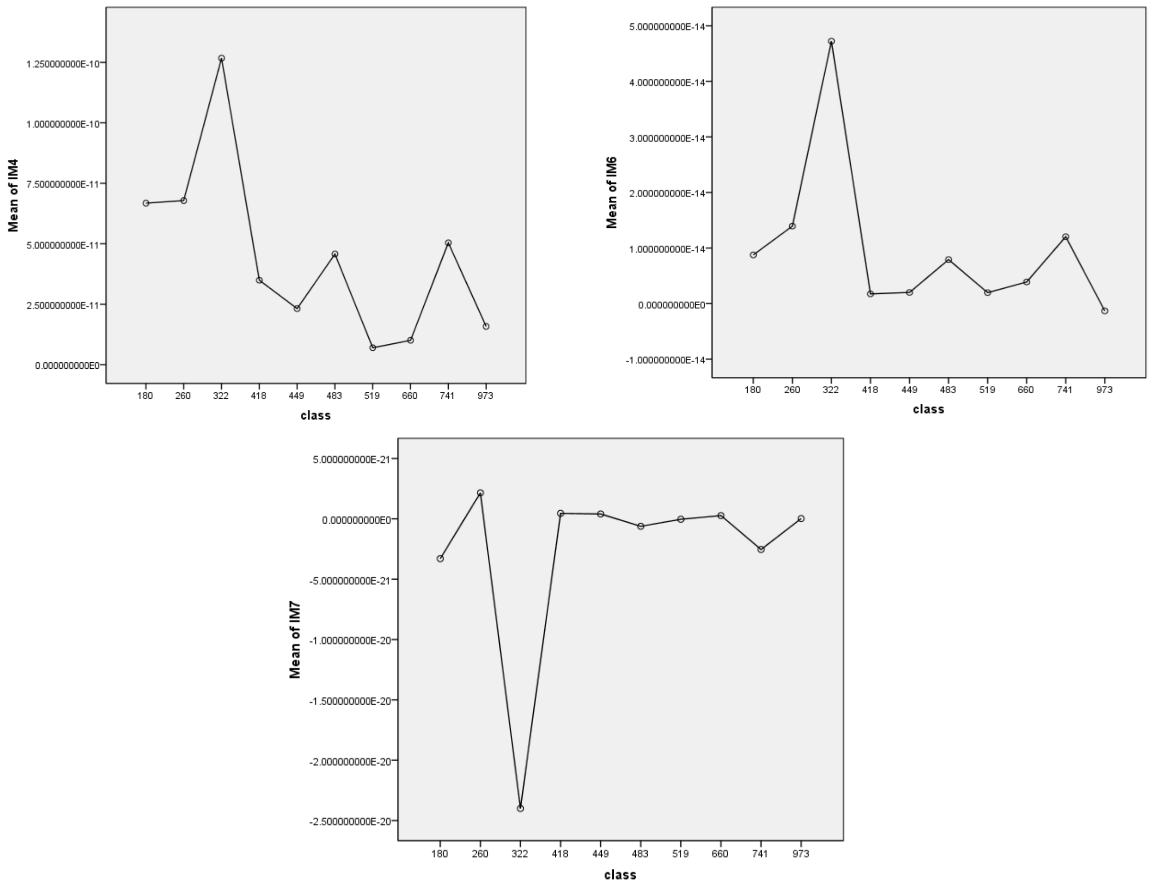


Figure 4: Mean Plots of Features.

We demonstrated the possibility of ordering the features using F-statistics in this article. In our example, the feature “mean” is not able to distinguish two image classes in post-hoc analysis because they have the same mean. Thus there is a need to elicit the knowledge to distinguish image classes that do not differ significantly. Thus there is a need for probing additional knowledge to distinguish the image classes. Simply confining to this procedure of extracting significant features for distinguishing the image classes is insufficient.

CONCLUSIONS

We prove our statistical features significance, not by using axiomatic approach, not by an experimental approach, not by using modeling, or not by simulation approach. We are analyzing and showing using data itself. This is a data science approach. Thus our work in this article starts with the exploratory data analysis on the benchmark BioIDface (expression) data set.

An illustration of the extraction of features, their descriptive statistics on a test sample of 10 images are given. An analysis of variance was carried out on all extracted features to know which of these features are significant. The significant features are then ranked. A post-hoc analysis is carried on each feature to see which pair of image classes differ significantly under each feature. Simply confining to this procedure of extracting significant features for distinguishing the image classes which is insufficient is established in this article.

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