Gender Detection

Selen Akkaya s289332

January 2023

Abstract

In this paper, 'synthetic speaker embeddings that represent the acoustic characteristics of a spoken utterance' is analyzed and a gender classification task is applied by building commonly used machine learning algorithms. Moreover, the performances of applied machine learning models and the comparison of models are analyzed.

1 Introduction

1.1 Problem Overview

The data-set contains synthetic speaker embeddings which represent the acoustic characteristics of a spoken utterance. Each row corresponds to a different speaker and contains **12 features** followed by the gender label:
1: female,
0: male
The features do not have any particular interpretation. Speakers belong to four different age groups. The age information, however, is not available.
The **training set** consists of **3000** samples for each class, whereas the **test set** contains **2000** samples for each class.

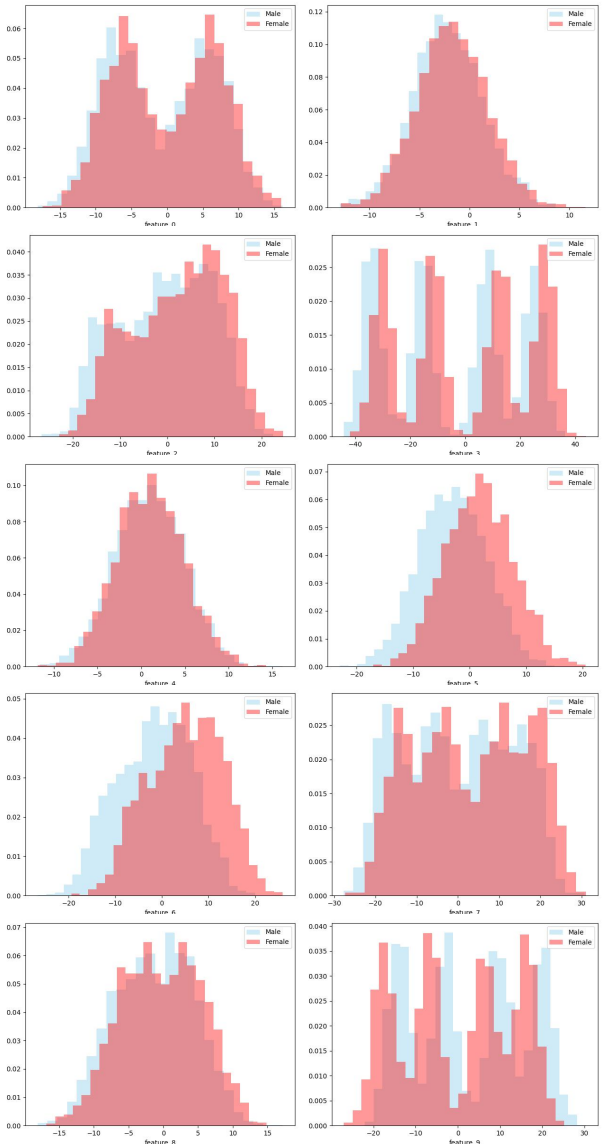
1.2 Exploratory Data Analysis

The 12 features are in a scale that have considerably similar means and variances, so it does not worth to apply Z-normalization which is basically centering every feature to its mean and scaling to unit variance xi = (xi-μ) / σ

μ : [-0.40439904, -1.98045219, 0.84747715, -2.37863374, 0.97348671, -0.72096827, 1.684338, 1.49200716, -0.8046595, 1.31572434, -0.07712583, 1.00468738]

σ : [7.09209235, 3.52880203, 9.8027367, 23.02600239, 3.85825232, 6.35299195, 8.5832784, 13.35106596, 5.71561775, 13.29758557, 10.69372272, 6.69376688]

Histograms of each 12 features (raw data) are shown below as Figure 1. It is obvious that raw features have approximated Gaussian distribution.



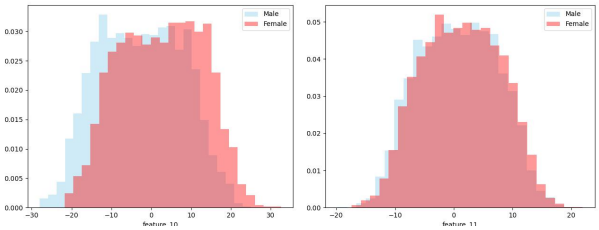


Figure 1: Raw Features

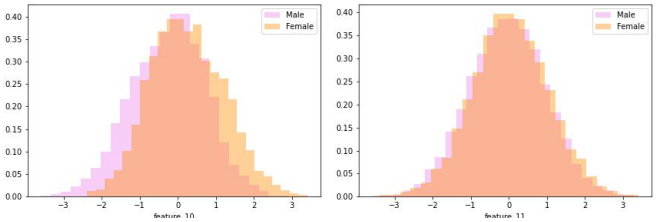
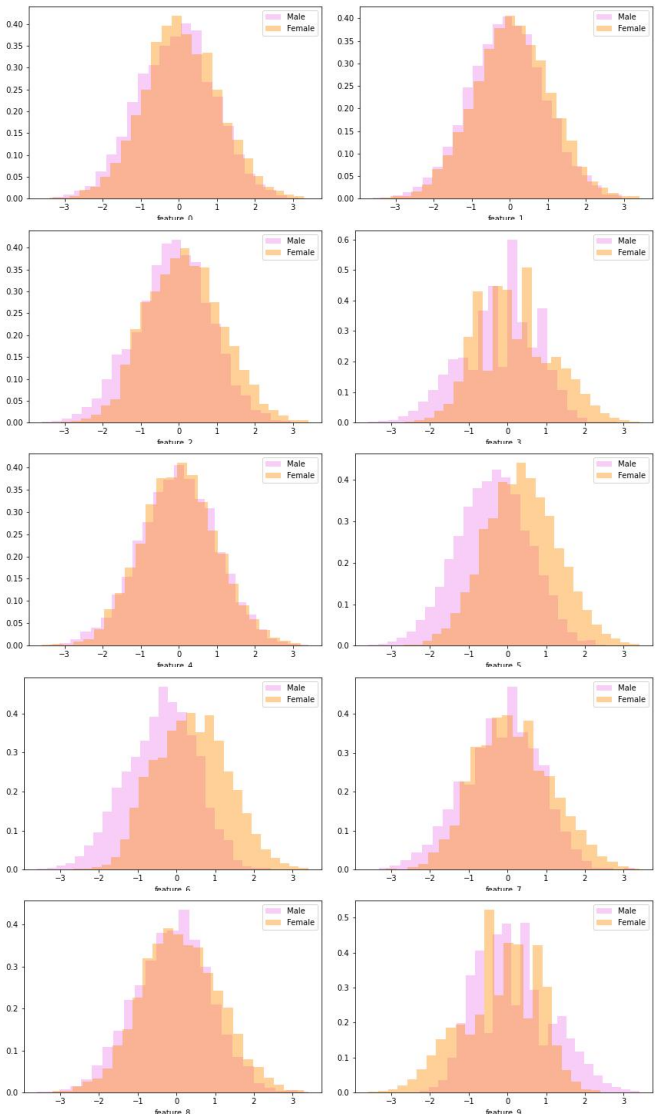


Figure 2: Gaussianized Features

However, to approve this idea, histograms of Gaussianized features are plotted to demonstrate. Every 12 features with Gaussianization as it is shown in Figure 2.



The gaussianization did not improve the histograms. Using raw data is better in this case. Especially feature-3 and feature-9 show how gaussianization worsens the result compared to the raw data.

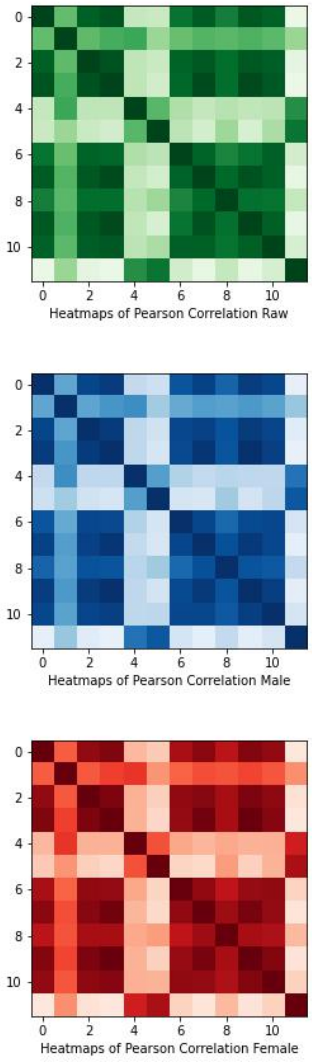


Figure 3: : Heatmap - Pearson Correlation

Pearson Correlation Heatmap shows that there are strongly corrolated features for instance, feature 3 is highly correlated to the 0, 2, 7 and 9. As an another example, feature 10 has a reasonable correlation with 0, 2, 3, 6, 7 and 9. Therefore, we can benefit of PCA to reduce dimension and map data to less correlated features.

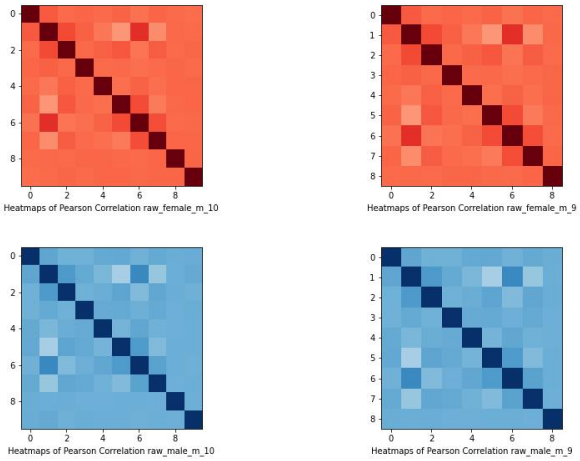


Figure 4: : Heatmap - Pearson Correlation with PCA m=10 and PCA m=9

2 Classification

In this report, the following machine learning models will be implemented and collected outputs will be compared:

- Multivariate Gaussian Classifier (MVG)
- Logistic Regression
- Support Vector Machine
- Gaussian Mixture Models

K-Fold cross validation is applied to all the models in this paper, with K=5 in order to clarify which model is most promising.

2.1 Multivariate Gaussian Classifiers

Samples of each class (male, female) can be modeled as samples of Multivariate Gaussian Classifiers (MVG) with class dependent mean and covariance matrices.
In particular, with the covariance matrices that are Full Covariances, Tied Covariance, Diagonal Covariances. These are generative models with Gaussian distributed data, given the class, as:

$$X|C = c \sim N(\mu_c, \Sigma_c)$$

Tied Multivariate Gaussian Classifiers assume that each class has its own mean, but the covariance matrix is the same for all classes.

$$X|C = c \sim N(\mu_c, \Sigma)$$

Naive Bayes version of MVG is simply a Gaussian Classifier where the covariance matrices are diagonal. We can adopt MVG by simply zeroing the out-of-diagonal elements of MVG solution.

It is obvious from previous histograms that features approximately have a gaussian distribution. Therefore, Generative Models should work well with our dataset.
Apart from that, it is expected to have poor performance from the Naive Bayes classifier since heatmaps show that correlation is significantly spreaded between the features.

– MVG, Full Covariance - Untied
– MVG, Naive Bayes - Untied
– MVG, Full Covariance - Tied
– MVG, Naive Bayes - Tied

The results that are obtained are below (for Gaussian Classifiers) for Raw features, Z-normed features and Gaussianized features. It is shown with different applications (ours has $\pi = 0.5$) with π=0.5, π=0.1 and π=0.9:
no PCA, PCA-m=10 and PCA-m=10
5 folds

Table 1: RAW Features, no PCA

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Full Covariance - Untied	0.048	0.126	0.123
Naive Bayes - Untied	0.565	0.818	0.848
Full Covariance - Tied	0.048	0.125	0.127
Naive Bayes - Tied	0.566	0.821	0.845

Table 2: Z-Normalized Features, no PCA

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Full Covariance - Untied	0.048	0.126	0.123
Naive Bayes - Untied	0.565	0.818	0.848
Full Covariance - Tied	0.048	0.125	0.127
Naive Bayes - Tied	0.566	0.821	0.845

In overall, full covariance matrices perform better than diagonal covariance matrices. This was expected because of highly correlated features.

PCA gives a good result even with m=9. It was

Table 3: Gaussianized Features, no PCA

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Full Covariance - Untied	0.062	0.181	0.171
Naive Bayes - Untied	0.541	0.810	0.824
Full Covariance - Tied	0.060	0.180	0.167
Naive Bayes - Tied	0.538	0.804	0.816

Table 4: RAW Features, PCA m = 10

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Full Covariance - Untied	0.047	0.140	0.120
Naive Bayes - Untied	0.067	0.173	0.161
Full Covariance - Tied	0.048	0.131	0.124
Naive Bayes - Tied	0.067	0.166	0.158

Table 5: Z-Normalized Features, PCA m = 10

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Full Covariance - Untied	0.112	0.140	0.120
Naive Bayes - Untied	0.119	0.173	0.161
Full Covariance - Tied	0.111	0.131	0.124
Naive Bayes - Tied	0.118	0.166	0.158

Gaussianized Features, PCA m = 10,

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Full Covariance - Untied	0.071	0.206	0.204
Naive Bayes - Untied	0.085	0.228	0.223
Full Covariance - Tied	0.071	0.199	0.206
Naive Bayes - Tied	0.083	0.227	0.225

Table 6: RAW Features, PCA m = 9

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Full Covariance - Untied	0.046	0.137	0.121
Naive Bayes - Untied	0.067	0.171	0.159
Full Covariance - Tied	0.047	0.130	0.122
Naive Bayes - Tied	0.066	0.163	0.158

Table 7: Z-Normalized Features, PCA m = 9

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Full Covariance - Untied	0.158	0.403	0.376
Naive Bayes - Untied	0.161	0.417	0.377
Full Covariance - Tied	0.155	0.398	0.367
Naive Bayes - Tied	0.161	0.415	0.376

expected since correlation is obvious between features (from heat-maps). Moreover, PCA improves the Naive Bayes performance. However it is not significant compared to full covariance models on RAW features. Apart from that, Z normalization features does not bring a remarkable result.

Table 8: Gaussianized Features, PCA m = 9

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Full Covariance - Untied	0.091	0.242	0.238
Naive Bayes - Untied	0.095	0.260	0.258
Full Covariance - Tied	0.090	0.236	0.233
Naive Bayes - Tied	0.096	0.260	0.261

2.2 Logistic Regression

Logistic Regression Classifier is a discriminative model. In this report Logistic Regression applied with linear separation rules and Quadratic Logistic Regression will be employed. The implemented objective function is:

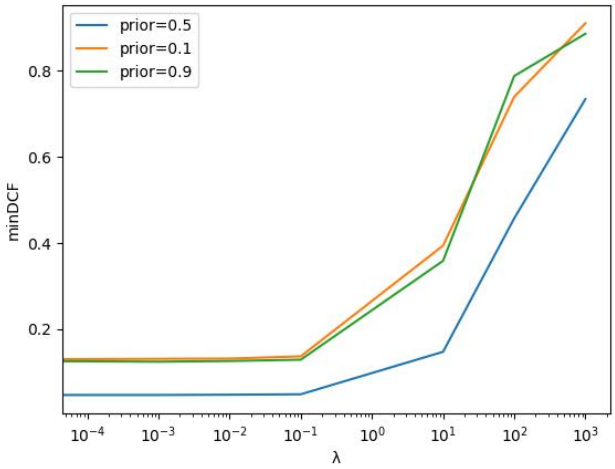
$$R(w) = \frac{\lambda}{2}\|w\|^2 + \frac{\pi_T}{n_T}\sum_{i|z_i=1} l(z_i s_i) + \frac{1-\pi_T}{n_F}\sum_{i|z_i=-1} l(z_i s_i)$$

Logistic Regression in this version applies linear separation. However, we can also define non-linear separation by building a specific expanded feature space defined as:

$$\phi(\boldsymbol{x}) = \begin{bmatrix} \text{vec}\left(\boldsymbol{x}\boldsymbol{x}^T\right) \\ \boldsymbol{x} \end{bmatrix}$$

The plots show how minDCF is affected by different values of λ.

Figure 5: DCF- λ graph for LogReg with Raw features



Best value for λ seems 10^{-5}, that is why setting parameter to 10^{-5} seems reasonable decision.

In this version of Logistic Regression model, we are allowed to estimate quadratic separation surfaces in the original space.

It is expected to obtain a good result by Logistic Regression since 'Full Covariance - Tied' performs linear separation rules and consequently it provided a good result. Moreover, since Logistic Regression does not require a particular assumptions on the data distribution, we do not expect 'Z-normalization' and 'Gaussianization' to provide a remarkable improvement on the result.

All the parameters used to obtain results below are :

m: None, 11, 10

folds: 5,

pT: [0.5, 0.1, 0.9],

pi: [0.5, 0.1, 0.9],

l: 1e-4

Table 9: LogReg, Raw Features, no PCA

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
LR(λ=10^{-5},πT=0.5)	0.047	0.131	0.126
LR(λ=10^{-5},πT=0.1)	0.047	0.136	0.122
LR(λ=10^{-5},πT=0.9)	0.047	0.130	0.130
PCA m = 11			
	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
LR(λ=10^{-5},πT=0.5)	0.048	0.133	0.126
LR(λ=10^{-5},πT=0.1)	0.046	0.138	0.120
LR(λ=10^{-5},πT=0.9)	0.048	0.132	0.124
PCA m = 10			
	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
LR(λ=10^{-5}, πT=0.5)	0.048	0.139	0.122
LR(λ=10^{-5}, πT=0.1)	0.048	0.145	0.121
LR(λ=10^{-5}, πT=0.9)	0.049	0.140	0.124

Table 10: LogReg, Gaussianized Features, no PCA

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
LR(λ=10^{-5},πT=0.5)	0.056	0.163	0.158
LR(λ=10^{-5},πT=0.1	0.055	0.172	0.166
LR(λ=10^{-5},πT=0.9	0.057	0.170	0.160
PCA m = 11			
	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
LR(λ=10^{-5},πT=0.5)	0.068	0.185	0.188
LR(λ=10^{-5},πT=0.1	0.068	0.191	0.197
LR(λ=10^{-5},πT=0.9	0.068	0.191	0.197
PCA m = 10			
	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
LR(λ=10^{-5},πT=0.5)	0.068	0.193	0.196
LR(λ=10^{-5},πT=0.1	0.067	0.194	0.202
LR(λ=10^{-5},πT=0.9	0.070	0.192	0.204

Table 11: LogReg, Z-Normalized Features, no PCA

	$\pi = 0.5$	π= 0.1	$\pi = 0.9$
LR(λ=10^{-5},πT=0.5)	0.047	0.131	0.126
LR(λ=10^{-5},πT=0.1)	0.047	0.137	0.122
LR(λ=10^{-5},πT=0.9)	0.048	0.130	0.130
PCA m=11,			
	π= 0.5	$\pi = 0.1$	$\pi = 0.9$
LR(λ=10^{-5},πT=0.5)	0.096	0.261	0.224
LR(λ=10^{-5},πT=0.1)	0.098	0.260	0.222
LR(λ=10^{-5},πT=0.9)	0.096	0.266	0.229
PCA m=10			
	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
LR(λ=10^{-5},πT=0.5)	0.113	0.294	0.260
LR(λ=10^{-5},πT=0.1)	0.113	0.301	0.257
LR(λ=10^{-5},πT=0.9)	0.112	0.299	0.258

The results of adjusting the hyper-parameter λ indicate that regularization is necessary and advantageous, with the best results achieved for low values. However, as λ approaches 1, the results begin to deteriorate. The study has now shifted to examining the results for various values of πT, which are found to be quite similar.

2.2.1 Quadratic Logistic Regression

Quadratic Logistic Regression is a variant of LogReg where the link between the predictor and the log odds of the target is represented as a quadratic instead of a linear function. This quadratic term enables modeling non-linear connections between the predictor and target variables.

Figure 6: DCF- λ graph for Quadratic LogReg with Raw features

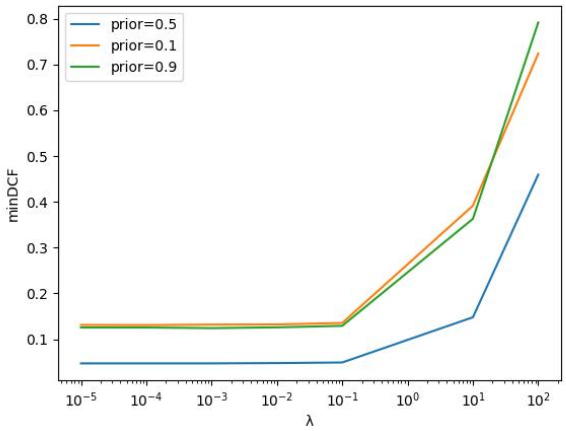
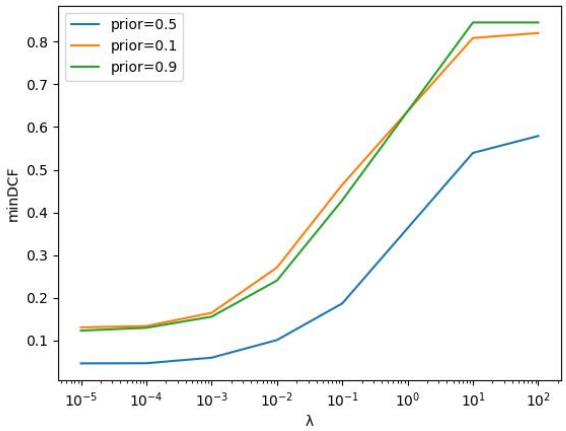


Figure 7: DCF- λ graph for Quadratic LogReg with normalized features



All the parameters used to obtain results below are :

m: None, 10 ; **folds:** 5; **pT:** [0.5, 0.1, 0.9] ; **pi:** [0.5, 0.1, 0.9]; **l:** 1e-5

Figure 8: DCF- λ graph for Quadratic LogReg with gaussianized features

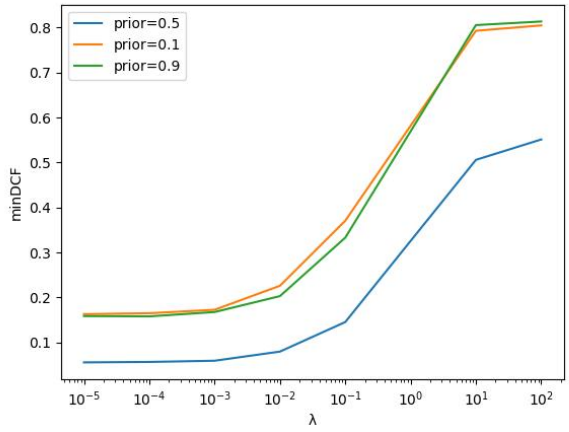


Table 12: Quadratic LogReg, Raw Features, PCA m = 10

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Q-LR(λ=10^{-5},πT=0.5)	0.048	0.139	0.122
Q-LR(λ=10^{-5},πT=0.1)	0.049	0.145	0.120
Q-LR(λ=10^{-5},πT=0.9)	0.049	0.140	0.124

Table 13: Quadratic LogReg, Normalized Features, PCA m = 10

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Q-LR(λ=10^{-5},πT=0.5)	0.112	0.295	0.260
Q-LR(λ=10^{-5},πT=0.1)	0.114	0.301	0.257
Q-LR(λ=10^{-5},πT=0.9)	0.112	0.299	0.259

Table 14: Quadratic LogReg, Gaussianized Features, PCA m = 10

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Q-LR(λ=10^{-5},πT=0.5)	0.068	0.193	0.198
Q-LR(λ=10^{-5},πT=0.1)	0.067	0.195	0.203
Q-LR(λ=10^{-5},πT=0.9)	0.070	0.193	0.204

In summary, linear decision rules are found to be more effective in separating classes. The research on this application is ongoing, with the focus on training Support Vector Machines (SVMs) and Gaussian Mixture Models (GMMs). The first method to be used will be SVMs, and it is anticipated that the results will be positive.

2.3 Support Vector Machine

The Support Vector Machine is a discriminative classifier. An SVM is a supervised learning algorithm that is used for classification and regression tasks. It aims to do a hyperplane separation of two classes with the maximum margin. It works by finding the hyperplane in a high-dimensional space that maximally separates the data points into different classes. The model: Linear SVM needs an hyper-parameter tuning for C via cross-validation while employing different values of C for the two classes.

In this paper, 3 different SVMs will consider:
- Linear Support Vector Machine
- Polynomial quadratic kernel degree=2
- Radial Basis Function kernel formulations

2.3.1 Linear SVM

In the case of a linear SVM, the hyperplane is a linear boundary that separates the data points: The linear SVM model is searching for a hyperplane with largest margin and a hyper plane that correctly separates as many instances as possible. The problem is that you will not always able to get both. The C parameter determines how great your desire is for finding a hyperplane that correctly separates as many instances as possible. (low C : large margin, high C : much smaller margin). Therefore C parameter defines a trade-off .

The following graphs show how minDCF varies depending on different values of the hyperparameter C.

All the parameters used to obtain results below are :

m: None (PCA not applied)

gaussianization: "no",

normalization: "yes",

folds: "5 folds",

mode: "Linear",

K: 1.0,

pT: 0.5

pi: [0.5, 0.1, 0.9],

C: [0.0001, 0.001, 0.01, 0.1, 1]

Setting C=1.0 gives the best results.minDCF values with different values of C is reported above with graphs on normalized and gausianized dataset.

Figure 9: DCF Linear SVM with Normalized features

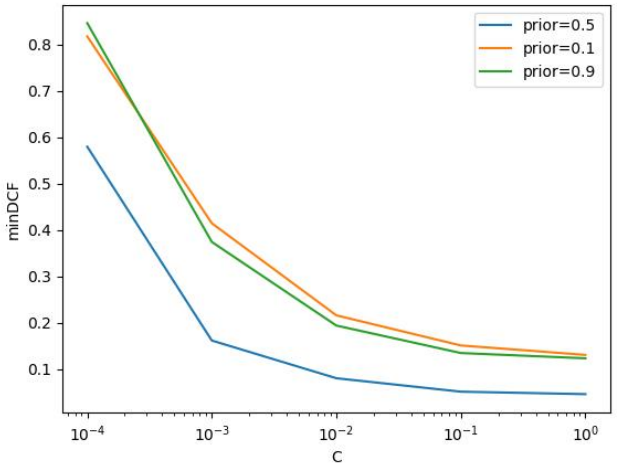


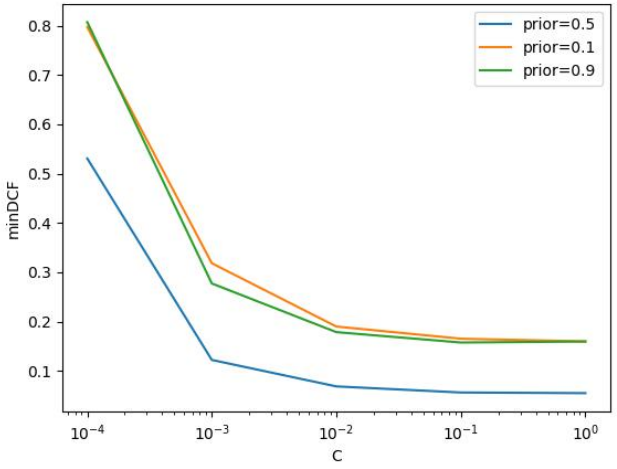
Table 15: Linear SVM, Norm-Features, no PCA, πT=0.5

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
L-SVM, C:0.01, K=1.0	0.080	0.216	0.194
L-SVM, C:0.1, K=1.0	0.051	0.151	0.135
L-SVM, C:1, K=1.0	0.046	0.131	0.123
L-SVM, C:10, K=1.0	0.066	0.190	0.178

Table 16: Linear SVM, Gau-Features, no PCA, πT=0.5

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
L-SVM, C:0.01, K:1.0	0.069	0.190	0.179
L-SVM, C:0.1, K:1.0	0.056	0.165	0.158
L-SVM, C:1, K:1.0	0.055	0.160	0.160
L-SVM, C:10, K:1.0	0.059	0.165	0.160

Figure 10: DCF-C graph for Linear SVM with Gausianized features



2.3.2 Quadratic SVM - Polynomial kernel function with degree=2

One of the non-linear SVM model used is the polynomial quadratic kernel:

$$k(x1, x2) = (x1^T x2 + c)^d$$

where d is the degree that is set as 2 (quadratic)

Regularized bias is added to the non - linear SVM as a constant value K to the kernel function.

Figure 11: DCF-C graph for Quadratic SVM with Gausianized features

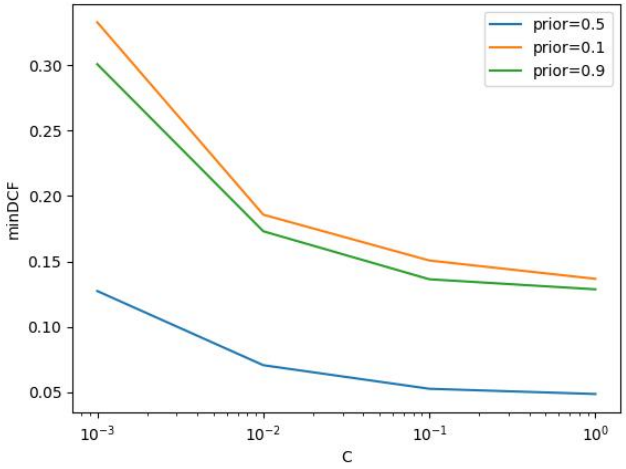


Table 17: Quadratic SVM, Normalized-Features, no PCA, πT=0.5, K=0.1

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Quad SVM, C: 0.01	0.071	0.183	0.171
Quad SVM, C: 0.1	0.053	0.149	0.139
Quad SVM, C :1.0	0.046	0.138	0.128
Quad SVM, C: 10	0.046	0.149	0.135

Quadratic SVM, Normalized-Features, no PCA, πT=0.5, K=1.0

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
Quad SVM, C: 0.01	0.071	0.186	0.173
Quad SVM, C: 0.1	0.053	0.151	0.136
Quad SVM, C: 1	0.049	0.137	0.129
Quad SVM, C: 10	0.048	0.141	0.134

2.3.3 RBF SVM - Radial Basis kernel SVM

In the context of support vector machines (SVMs), the term "RBF" stands for radial basis function. An RBF SVM is a type of SVM that uses an RBF kernel to perform non-linear classification.

RBF SVM is capable of finding non-linear boundaries by using an RBF kernel.

The radial basis function (RBF) kernel is a function that measures the similarity between two data points based on their distance from a central point, or "center." The RBF kernel is defined as follows:

$$K(\mathbf{x}, \mathbf{y}) = \exp\left(-\frac{|\mathbf{x} - \mathbf{y}|^2}{2\sigma^2}\right)$$

where $\mathbf{x}$ and $\mathbf{y}$ are data points, and σ is a free parameter that controls the width of the kernel.

In some cases, the RBF kernel is defined with an additional parameter called γ, which is defined as follows:

$$K(\mathbf{x}, \mathbf{y}) = \exp\left(-\gamma|\mathbf{x} - \mathbf{y}|^2\right)$$

The value of γ determines the shape of the decision boundary and has a significant impact on the performance of the model. A larger value of γ results in a more complex decision boundary, while a smaller value results in a simpler boundary.

The RBF kernel allows the SVM to learn a non-linear decision boundary by mapping the data points to a higher-dimensional space using the kernel function. In this higher-dimensional space, the SVM can find a linear boundary that separates the data points.

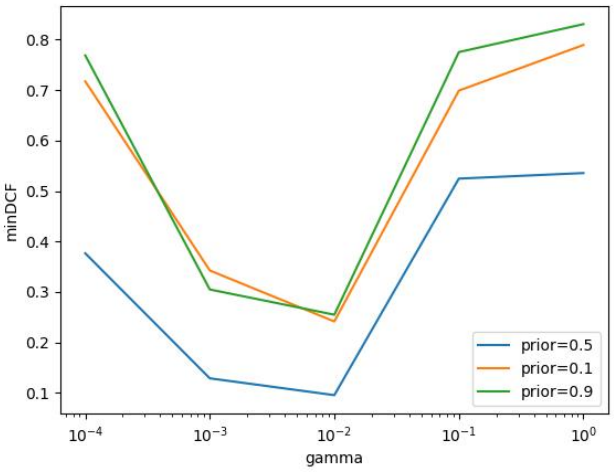
Class balancing did not make a huge difference that is why keeping the model without class balancing was considered while results are obtaining.

According to the graph above : gamma-minDCF graph for RBF SVM with Normalized features, best value for γ seems 10^-2 when k=1.0 and c=1.0

Table 18: RBF SVM, Gausianized-Features, no PCA, πT=0.5, gamma : 10^-2

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
RBF SVM, C: 0.1, K=1.0	0.116	0.304	0.285
RBF SVM, C: 1.0, K=1.0	0.082	0.219	0.212
RBF SVM, C: 10, K=1.0	0.146	0.375	0.353

Figure 12: gamma-minDCF graph for RBF SVM with Normalized features



2.3.4 Comparison of well performed Models w.r.t. minDCF:

Comparison of linear models that is discussed in this report is shown below :

MVG (Tied Full-Cov)
Log Reg (= 105,T = 0.5)
Linear SVM C=1.0

Table 19: Gausianized-Features, no PCA, πT=0.5,

	π = 0.5	π = 0.1	π= 0.9
MVG (Tied Full-Cov)	0.048	0.125	0.127
LogReg(= 10^5,πT =0.5)	0.047	0.131	0.126
Linear SVM, C=1.0	0.046	0.131	0.123

2.3.5 Comparison of MVG Tied Full-Cov and LogReg w.r.t. minDCF:

Linear LR performs similar to MVG Tied Full-Cov. However Linear Logistic regression performs slightly better in this case.

Reducing to 10 dimensions, does not affect on performance dramatically.

Table 20: LR(λ=10^{-5} and MVG Tied Full-Cov, Raw Features, no PCA

	π = 0.5	π= 0.1	π = 0.9
LR(λ=10^{-5},πT=0.5)	0.047	0.131	0.126
MVG Full Cov-Tied	0.048	0.125	127

Table 21: LR(λ=10^{-5} and MVG Tied Full-Cov, Raw Features, PCA m=10

	π = 0.5	π= 0.1	π = 0.9
LR(λ=10^{-5}, πT=0.5)	0.048	0.139	0.122
Full Covariance - Tied	0.048	0.131	0.124

2.4 Gaussian Mixture Model

GMM is a probabilistic model that assumes observed data is generated from a mixture of several underlying distributions that each is a Gaussian distribution.

To fit a GMM to a dataset, the model's parameters must be estimated from the data. This is typically done by using an iterative algorithm, such as the Expectation-Maximization (EM) algorithm.

The EM algorithm estimates the parameters of the GMM by iteratively updating the estimates of the means, variances, and mixing coefficients of the underlying Gaussian distributions. The GMM is defined by a set of parameters, including:
Mixing coefficients, Means, Covariances:The covariances can be represented using a diagonal matrix or a full covariance matrix.

The GMM is a probabilistic model that assumes that the underlying data is generated from a mixture of a finite number of K Gaussian distributions, where each Gaussian distribution is a component of the model. The component parameter in a GMM is the number of Gaussian distributions, or components, that are used to model the data.

In this paper GMM is reported with 2, 4 and 8 components but it could be tested also with higher components. Since validation of the model is computationally very expensive, keeping the number of components to a reasonably small values seems feasible.

– Gaussian Mixture Models (GMM)
– GMM + Full Covariance
– GMM + Diagonal Covariance
– GMM + Tied Covariance
– GMM + Diagonal Covariance with Tied Covariance

Table 22: Raw-Features, no PCA, π=0.5,

Components	2	4	8
Full - Covariance	0.044	0.033	0.032
Full - Covariance - Tied	0.043	0.033	0.030
Diag - Covariance	0.400	0.108	0.087
Diag - Covariance - Tied	0.400	0.108	0.082

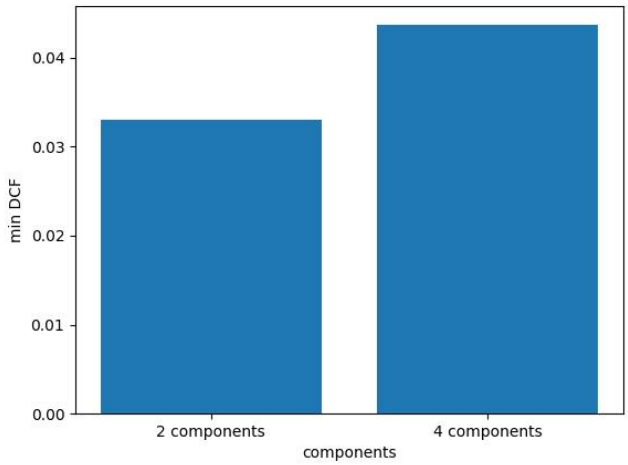
Table 23: Gausianized-Features, no PCA, π=0.5,

Components	2	4	8
Full - Covariance	0.053	0.047	0.048
Full - Covariance - Tied	0.053	0.047	0.050
Diag - Covariance	0.346	0.127	0.106
Diag - Covariance - Tied	0.346	0.127	0.106

Table 24: Raw-Features, PCA m = 10, π=0.5,

Components	2	4	8
Full - Covariance	0.072	0.051	0.056
Full - Covariance - Tied	0.072	0.051	0.056
Diag - Covariance	0.085	0.097	0.096
Diag - Covariance - Tied	0.085	0.097	0.096

Figure 13: GMM components - minDCF graph for full untied model



(For computational reasons, only 2 and 4 components were taken into consideration for plotting the graph.)

As a conclusion the best result is obtained with Full - Covariance - Tied GMM with 8 components. Also raw features gave the best results compared to gausianized features. In addition, dimensionality reduction did not benefit on full covariance types of GMM wheres it benefit on Diagonal covariance versions.

3 Score Calibration

In this part of the report, ROC curve and Bayes Error will be considered.

The Bayes error rate is the lowest possible error rate that can be achieved by a classifier, assuming that the classifier has access to the true underlying probability distribution of the data. In other words, it is the minimum error rate that can be achieved by a classifier when the classifier makes predictions based on the most accurate possible knowledge of the data.

The ROC curve allows you to visually assess the trade-off between the true positive rate and the false

positive rate of a classifier, and can be used to compare the performance of different classifiers.

3.1 MVG - Score Calibration

Comparison of minDCF and the actual DCF of the models that have been shown so far in this report.

Bayes error plots shows the distance between minDCF and actDCF for MVG full covariance Tied on Normalized features which was one of the best MVG model w.r.t. the results that are obtained.

Figure 14: Bayes Error Plot for MVG - full cov. - tied on Normalized features.

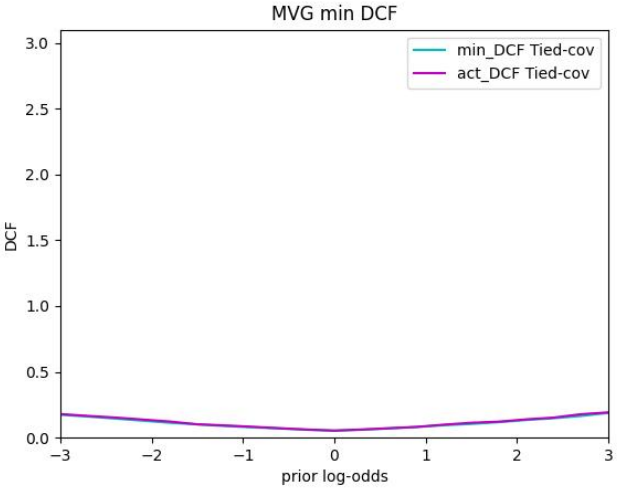
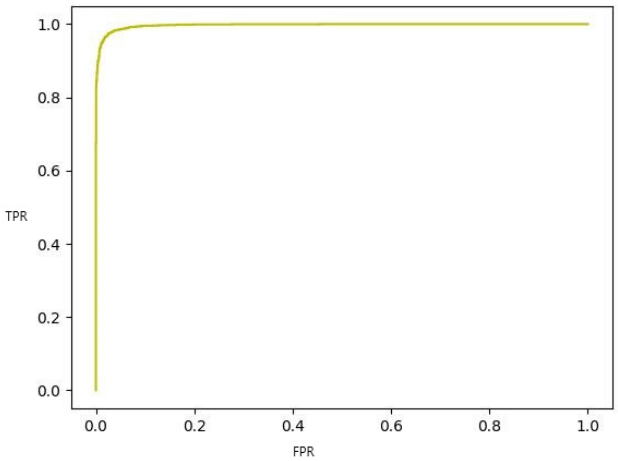


Figure 15: ROC curve of MVG - full cov. - tied on Normalized features.



A classifier with a higher true positive rate and a lower false positive rate will have a ROC curve that is located closer to the top left corner of the plot, indicating better performance.
According to the ROC curve our classifier performed well.

3.2 LR - Score Calibration

Bayes error plots show a considerable distance between minDCF and actDCF for Linear Logistic Regression. However according to the ROC curve our classifier performed well.

Figure 16: Bayes Error Plot for Linear LR - on Normalized features.

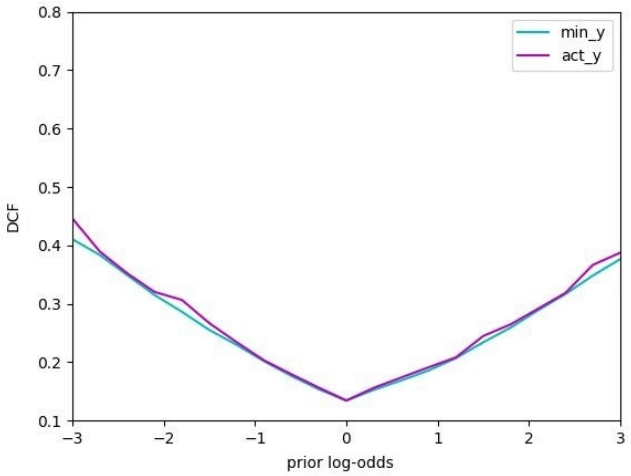
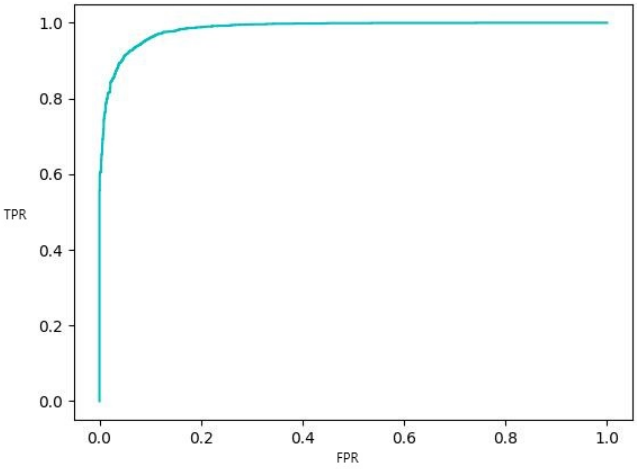


Figure 17: ROC curve Linear LR - on Normalized features.



3.3 SVM - Score Calibration

Bayes error plots shows the distance between minDCF and actDCF for Linear SVM - on Normalized features which was one of the best GMM model w.r.t. the results that are obtained.

Figure 18: Bayes Error of Linear SVM - on Normalized features.

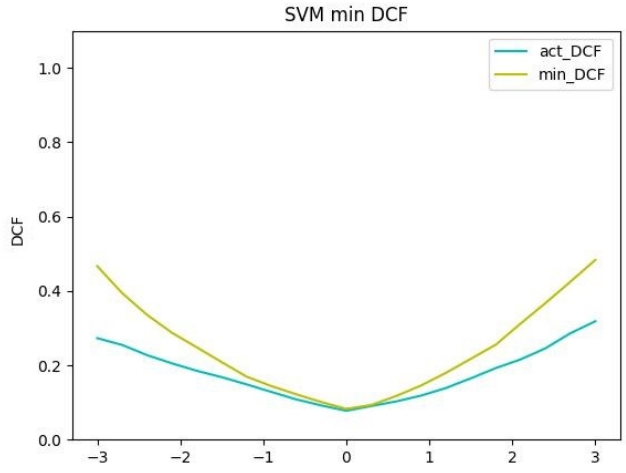
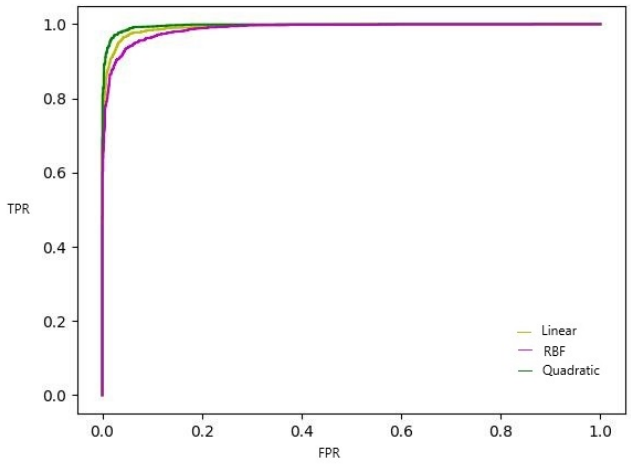


Figure 19: ROC curve of SVM for linear, polynomial and RBF kernel - on Normalized features.



According to the ROC curve our classifier performed well with all the kernels. Linear SVM and quadratic SVM performed similarly well wheres RBF performed worse.

3.4 GMM - Score Calibration

Bayes error plots shows the distance between minDCF and actDCF for GMM with 8 components - on Gausianized features which was one of the best GMM model w.r.t. the results that are obtained.

Figure 20: Bayes Error curve of GMM with 8 components - on Normalized features.

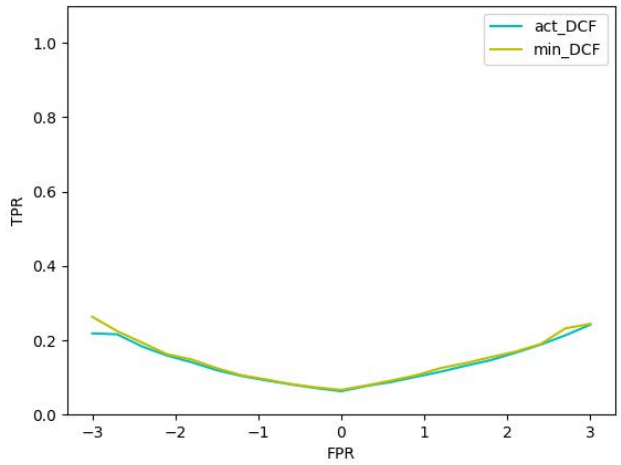
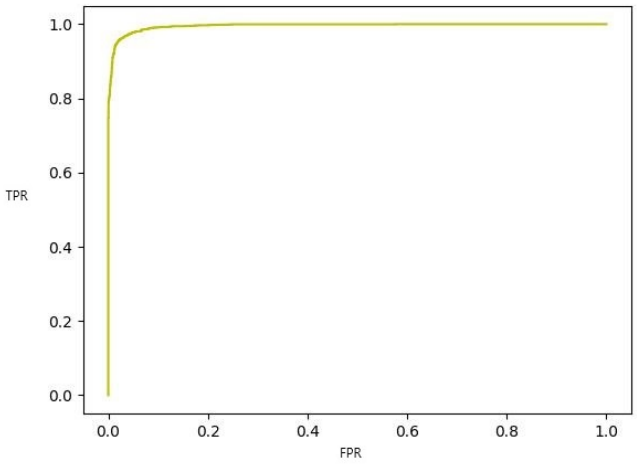


Figure 21: ROC curve of GMM with 8 components - on Normalized features.



According to the ROC curve GMM with 8 components performed well.

4 Experimental results and Conclusion

In this section of the report, the in-so-far best classifiers will be considered with test dataset.
minDCF will be considered to verify the proposed solution can achieve the best accuracy.

Table 25: Norm-Features, no PCA

	$\pi = 0.5$	$\pi = 0.1$	$\pi = 0.9$
MVG Tied Full Cov	0.050	0.132	0.135
Linear LR	0.052	0.135	0.133

Table 26: Raw-Features, no PCA, π=0.5,

Components	cmp=2	cmp=4	cmp=8
Full - Covariance	0.044	0.033	0.032
Full - Covariance - Tied	0.043	0.033	0.030

Test data yielded similar results. However GMM Full Covariance with 8 component seems the best with Raw features. Therefore it is reasonable to say that Linear models as well as gaussian mixture models proved to fit our dataset.