DISCRIMINANT ANALYSIS OF MULTI SENSOR DATA FUSION BASED ON PERCENTILE FORWARD FEATURE SELECTION

MAZ JAMILAH BINTI MASNAN

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Awang Had Salleh
Graduate School
of Arts And Sciences

Universiti Utara Malaysia

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Abstrak

Penyarian fitur ialah satu kaedah yang digunakan secara meluas untuk mengekstrak fitur yang signifikan dalam masalah gabungan data pelbagai penderia. Namun demikian, penyarian fitur mempunyai beberapa kelemahan. Masalah utamanya ialah kegagalan untuk mengenal pasti fitur diskriminatif dalam data multi kumpulan. Justeru, kajian ini mencadangkan satu analisis diskriminan gabungan data pelbagai penderia yang baharu menggunakan jarak Mahalanobis tak terbatas dan terbatas untuk menggantikan kaedah penyarian fitur dalam gabungan data pelbagai penderia peringkat rendah dan pertengahan. Kajian ini juga turut membina kaedah pemilihan fitur persentil kehadapan (PFPK) untuk mengenal pasti fitur diskriminatif tersaur untuk pengelasan data penderia. Prosedur cadangan pengelasan diskriminasi bermula dengan pengiraan purata jarak antara multi kumpulan menggunakan jarak tak terbatas dan terbatas. Kemudian, pemilihan fitur dimulakan dengan memberi pangkat kepada gabungan fitur dalam peringkat rendah dan pertengahan berdasarkan jarak yang dikira. Subset fitur telah dipilih menggunakan PFPK. Peraturan pengelasan yang dibina diukur menggunakan ukuran kejituan pengelasan. Keseluruhan penyiasatan telah dijalankan ke atas sepuluh data penderia *e-nose* dan *e-tongue*. Dapatan menunjukkan bahawa jarak Mahalanobis terbatas lebih superior dalam memilih fitur yang penting dengan bilangan fitur yang sedikit berbanding kriterium jarak tak terbatas. Tambahan pula, dengan pendekatan jarak terbatas, pemilihan fitur menggunakan PFPK memperolehi kejituan pengkelasan yang tinggi. Keseluruhan prosedur yang dicadangkan didapati sesuai untuk menggantikan analisis diskriminan gabungan data pelbagai penderia tradisional berdasarkan kuasa diskriminatif yang besar dan kadar penumpuan yang pantas pada kejituan pengelasan yang tinggi. Kesimpulannya, pemilihan fitur boleh menyelesaikan masalah penyarian fitur. Kemudian, PFPK yang dicadangkan terbukti efektif dalam memilih subset fitur dengan kejituan yang tinggi serta pengiraan pantas. Kajian ini juga menunjukkan kelebihan jarak Mahalanobis tak terbatas dan terbatas dalam pemilihan fitur bagi data berdimensi tinggi yang bermanfaat kepada kedua-dua jurutera dan ahli statistik dalam teknologi penderia.

Kata Kunci : Analisis Diskriminan, Gabungan Data Pelbagai Penderia, Jarak Mahalanobis Tak terbatas, Jarak Mahalanobis Terbatas, Pemilihan Fitur Persentil Kehadapan

Abstract

Feature extraction is a widely used approach to extract significant features in multi sensor data fusion. However, feature extraction suffers from some drawbacks. The biggest problem is the failure to identify discriminative features within multi-group data. Thus, this study proposed a new discriminant analysis of multi sensor data fusion using feature selection based on the unbounded and bounded Mahalanobis distance to replace the feature extraction approach in low and intermediate levels data fusion. This study also developed percentile forward feature selection (PFFS) to identify discriminative features feasible for sensor data classification. The proposed discriminant procedure begins by computing the average distance between multi-group using the unbounded and bounded distances. Then, the selection of features started by ranking the fused features in low and intermediate levels based on the computed distances. The feature subsets were selected using the PFFS. The constructed classification rules were measured using classification accuracy measure. The whole investigations were carried out on ten e-nose and e-tongue sensor data. The findings indicated that the bounded Mahalanobis distance is superior in selecting important features with fewer features than the unbounded criterion. Moreover, with the bounded distance approach, the feature selection using the PFFS obtained higher classification accuracy. The overall proposed procedure is found fit to replace the traditional discriminant analysis of multi sensor data fusion due to greater discriminative power and faster convergence rate of higher accuracy. As conclusion, the feature selection can solve the problem of feature extraction. Next, the proposed PFFS has been proved to be effective in selecting subsets of features of higher accuracy with faster computation. The study also specified the advantage of the unbounded and bounded Mahalanobis distance in feature selection of high dimensional data which benefit both engineers and statisticians in sensor technology.

Keywords : Bounded Mahalanobis Distance, Discriminant Analysis, Multi Sensor Data Fusion, Percentile Forward Feature Selection, Unbounded Mahalanobis Distance

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Glossary of Terms

Gustatory – relates to the sensations that arise from the stimulator of taste receptor cells found throughout the mouth or easily known as sense of taste.

Olfactory – the sense of smell mediated by specialized sensory cells of the nasal cavity of vertebrates.

Sensor data – the signals from specific sensor that has been preprocessed according to some suitable preferred methods.

Array sensor – a combination of sensors arranged in an array to overcome the problem of poor sensitivity and poor selectivity.

Features – or sometimes known as variables referring to the dimension of sensor data. Easily determined as the number of array sensors attached in a sensor

Group – or category is defined as a grouping of samples characterized by the same value of discrete variables or by contiguous values of continuous variables.

Non-selectivity – a situation where the qualitative and quantitative information are combined and the sensor response become highly ambiguous which makes the sensor unusable in real conditions when sensors are exposed to more than one analyte species.

Redundancy – occurrs as a consequence of the non-selectivity state where sensors are measuring the same response which makes the related sensors highly correlated

Low level data fusion – a state of combining different sensor data at the data level

Intermediate level data fusion – a state of combining different features of different sensor data at the feature level

High level data fusion – a state of combining the decisions of different sensors at the decision level

Classifier – or sometimes called as classification function is the rule used to allocate future object with an aim to minimize the misclassification rate over all possible allocations.

Training data set – is an independent data set used to train the classifier.

Test data set – is an independent data set used to evaluate training bias and estimate real performance of the constructed classifier.

List of Abbreviations

LLDF – Low Level Data Fusion

ILDF – Intermediate Level Data Fusion

HLDF – High Level Data Fusion

LDA – Linear Discriminant Analysis

QDA – Quadratic Discriminant Analysis

kNN – *k* Nearest Neighbor

ANN – Artificial Neural Network

PCA – Principal Component Analysis

PFFS – Percentile Forward Feature Selection

CHAPTER ONE
INTRODUCTION

1.1 Introduction

Discriminant analysis is a multivariate technique that explains the group membership as a function of multiple independent variables. The group membership is the dependent variable often appears as categorical value (nominal), while the independent variables which are often called as *discriminators* are usually in continuous form (interval or ratio). Wood, Jolliffe, and Horgan (2005) described discriminant analysis as a statistical technique that assigns observations to one of several distinct populations based on measurements made on the observations, or variables derived from the measurements. The process of allocating observations to their specific groups based on the constructed *discriminant rules* is called *classification*. The concept of discriminant analysis is rather exploratory in nature whereas the classification procedures are less exploratory, but leads to well-defined rules to allocate new observations.

The notion of discriminant analysis was introduced by Sir Ronald A. Fisher in the mid of 1930s. Then, it became an area of interest to other researchers in various disciplines in the 1950s and 1960s. Some researchers break up discriminant analysis into two parts; *predictive* discriminant analysis and *descriptive* discriminant analysis. Predictive discriminant analysis focuses on the prediction of group membership based on a subset of variables selected using certain criteria which are eventually assessed by the classification accuracy. On the contrary, descriptive discriminant analysis deals with assessing the independents variables that best explain the group separation which reflects the importance. Concisely, this work adapts both concepts

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Appendix A
DEVELOPED R ALGORITHMS FOR THE UNIVARIATE AND MULTIVARIATE MAHALANOBIS DISTANCES

A. Algorithms for fused feature ranking based on univariate unbounded Mahalanobis distance $\left(D^2\right)$

```
univariate.mahalanobisU <- function(variable, grouping)
{
  n <- nrow(variable)
  g <- as.factor(grouping)
  lev <- lev1 <- levels(g)
  counts <- as.vector(table(g))
  ng = length(lev1)
  group.mean <- aggregate(variable, by = list(groupFUN =
  "mean")
  xbargroup <- as.vector(group.mean)
  colnames(xbargroup) <- c("Group", "GroupMean")

  group.var <- aggregate(variable, by = list(grouping), FUN =
  "var") #group.var = data.frame
  vargroup <- as.vector(group.var)
  colnames(vargroup) <- c("Group", "GroupVariance")

  str(xbargroup)
  str(vargroup)

  Distance = matrix(nrow = ng, ncol = ng)
  dimnames(Distance) <- list(rownames(Distance, do.NULL =
  FALSE, prefix = "g"), colnames(Distance, do.NULL = FALSE,
  prefix = "g"))

  Means = round(xbargroup$GroupMean, digits=10)
  Variance = round(vargroup$GroupVariance digits=10)
  Distance = round(Distance, digits=3)

  for (i in 1:ng) {
    for (j in 1:ng) {
      if (i > j)

     Distance[i, j] <- ((Means[i]- Means[j])^2)*((counts[i]
     +counts[j])2) /(Variance[i]+Variance[j])
    }
  }
  return(Distance)
}
```

B. Algorithms for fused feature ranking based on univariate bounded Mahalanobis distance $\left(D_A^2\right)$

```
univariate.mahalanobisU <- function(variable, grouping)
{
  n <- nrow(variable)
  g <- as.factor(grouping)
  lev <- lev1 <- levels(g)
  counts <- as.vector(table(g))
  ng = length(lev1)
  group.mean <- aggregate(variable, by = list(groupFUN =
  "mean")
  xbargroup <- as.vector(group.mean)
  colnames(xbargroup) <- c("Group", "GroupMean")

  group.var <- aggregate(variable, by = list(grouping), FUN =
  "var") #group.var = data.frame
  vargroup <- as.vector(group.var)
  colnames(vargroup) <- c("Group", "GroupVariance")

  str(xbargroup)
  str(vargroup)

  Distance = matrix(nrow = ng, ncol = ng)
  dimnames(Distance) <- list(rownames(Distance, do.NULL =
  FALSE, prefix = "g"), colnames(Distance, do.NULL = FALSE,
  prefix = "g"))

  Means = round(xbargroup$GroupMean, digits=10)
  Variance = round(vargroup$GroupVariance digits=10)
  Distance = round(Distance, digits=3)

  for (i in 1:ng) {
    for (j in 1:ng) {
      if (i > j)

     Distance[i, j] <- ((Means[i]-Means[j])^2)*
     ((counts[i]+counts[j])-2)/(Variance[i]+ Variance[j])
     Distance[i, j] <- Distance[i, j]/(4+Distance[i, j])
     }
  }
  return(Distance)
}
```

C. Algorithms for multivariate unbounded Mahalanobis distance $\left(D^2\right)$

```
library(HDMD)
pairwise.MVmahal <- function (x, grouping, cov, inverted =
FALSE, digits = 3, ...)
{
  x <- if (is.vector(x))
    matrix(x, ncol = length(x))
  else as.matrix(x)
  if (!is.matrix(x))
    stop("x could not be forced into a matrix")
  if (length(grouping) == 0) {
    grouping = t(x[1])
    x = x[2:dim(x)[2]]
    cat("assigning grouping\n")
    print(grouping)
  }
  n <- nrow(x)
  p <- ncol(x)
  if (n != length(grouping)) {
    cat(paste("n: ", n, "and groups: ", length(grouping),
              "\n"))
    stop("nrow(x) and length(grouping) are different")
  }
  g <- as.factor(grouping)
  g
  lev <- lev1 <- levels(g)
  counts <- as.vector(table(g))
  if (any(counts == 0)) {
    empty <- lev[counts == 0]
    warning(sprintf(ngettext(length(empty), "group %s is
    empty", "groups %s are empty"), paste(empty, collapse = "
    ")), domain = NA)
    lev1 <- lev[counts > 0]
    g <- factor(g, levels = lev1)
    counts <- as.vector(table(g))
  }
  ng = length(lev1)
  group.means <- tapply(x, list(rep(g, p), col(x)), mean)
  #if (missing(cov)) {
  #if (is.null(poolcov)) {
  #inverted = FALSE
  #cov = cor(x)
  #  cov = poolcov(x)
  #}
  #else {
  #  if (dim(cov) != c(p, p))
  #    stop("cov matrix not of dim = (p,p)\n")
  #}
  Distance = matrix(nrow = ng, ncol = ng)
  dimnames(Distance) = list(names(group.means),
  names(group.means))
  Means = round(group.means, digits)
  Cov = round(cov, digits)
  Distance = round(Distance, digits)
```

```
  for (i in 1:ng) {
    Distance[i, ] = mahalanobis(group.means, group.means[i, ],
    cov, inverted)
  }
  result <- list(means = group.means, cov = cov, distance =
Distance)
  result
}
```

D. Algorithms for multivariate bounded Mahalanobis distance $\left(D_A^2\right)$

```
library(HDMD)
pairwise.MVmahal <- function (x, grouping, cov, inverted =
FALSE, digits = 3, ...)
{
  x <- if (is.vector(x))
    matrix(x, ncol = length(x))
  else as.matrix(x)
  if (!is.matrix(x))
    stop("x could not be forced into a matrix")
  if (length(grouping) == 0) {
    grouping = t(x[1])
    x = x[2:dim(x)[2]]
    cat("assigning grouping\n")
    print(grouping)
  }
  n <- nrow(x)
  p <- ncol(x)
  if (n != length(grouping)) {
    cat(paste("n: ", n, "and groups: ", length(grouping),
              "\n"))
    stop("nrow(x) and length(grouping) are different")
  }
  g <- as.factor(grouping)
  g
  lev <- lev1 <- levels(g)
  counts <- as.vector(table(g))
  if (any(counts == 0)) {
    empty <- lev[counts == 0]
    warning(sprintf(ngettext(length(empty), "group %s is
empty",
                             "groups %s are empty"),
paste(empty, collapse = " ")),
            domain = NA)
    lev1 <- lev[counts > 0]
    g <- factor(g, levels = lev1)
    counts <- as.vector(table(g))
  }
  ng = length(lev1)
  group.means <- tapply(x, list(rep(g, p), col(x)), mean)
  #if (missing(cov)) {
  #if (is.null(poolcov)) {
  #inverted = FALSE
  #cov = cor(x)
```

```
  #  cov = poolcov(x)
  #}
  #else {
  #  if (dim(cov) != c(p, p))
  #    stop("cov matrix not of dim = (p,p)\n")
  #}
  Distance = matrix(nrow = ng, ncol = ng)
  dimnames(Distance) = list(names(group.means),
names(group.means))
  Means = round(group.means, digits)
  Cov = round(cov, digits)
  Distance = round(Distance, digits)
  for (i in 1:ng) {
    Distance[i, ] = mahalanobis(group.means, group.means[i,
    ], cov, inverted)
  }
  result <- list(means = group.means, cov = cov, distance =
Distance)
  result
}
```

Appendix B
Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distances

Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distance for AS Honey

D^2				D_A^2			
Feature	Criterion Value	Rank	Percent	Feature	Criterion Value	Rank	Percent
N26	1937.62	1	100.00%	N15	0.9326	1	100.00%
N5	1872.11	2	97.50%	N5	0.9285	2	97.50%
N29	1815.44	3	95.10%	N23	0.9214	3	95.10%
N31	1116.44	4	92.60%	N11	0.9181	4	92.60%
N15	1086.9	5	90.20%	N29	0.914	5	90.20%
N9	1058.89	6	87.80%	N26	0.91	6	87.80%
N20	994.57	7	85.30%	N8	0.9099	7	85.30%
N16	928.61	8	82.90%	N18	0.9077	8	82.90%
N23	917.45	9	80.40%	N20	0.8984	9	80.40%
T11	888.82	10	78.00%	N2	0.8969	10	78.00%
N17	886.27	11	75.60%	N4	0.8965	11	75.60%
N13	832.86	12	73.10%	T11	0.8963	12	73.10%
N8	800.05	13	70.70%	N1	0.8916	13	70.70%
N21	779.23	14	68.20%	N3	0.8907	14	68.20%
N11	755.48	15	65.80%	N16	0.8883	15	65.80%
N18	727.66	16	63.40%	N31	0.8874	16	63.40%
N28	712.29	17	60.90%	N21	0.8834	17	60.90%
N7	626.57	18	58.50%	N9	0.882	18	58.50%
N12	616.34	19	56.00%	T2	0.8751	19	56.00%
N10	582.97	20	53.60%	N19	0.8743	20	53.60%
N1	580.04	21	51.20%	N13	0.8726	21	48.70%
N3	545.42	22	48.70%	N12	0.8726	22	48.70%
N4	516.91	23	46.30%	N14	0.8722	23	46.30%
N14	502.47	24	43.90%	N28	0.8555	24	43.90%
T2	498.87	25	41.40%	N25	0.8487	25	41.40%
N2	436.33	26	39.00%	N7	0.848	26	39.00%
N22	423.87	27	36.50%	T1	0.8386	27	36.50%
N25	405.44	28	34.10%	T3	0.8383	28	34.10%
N19	385.8	29	31.70%	T8	0.8379	29	31.70%
N27	347.33	30	29.20%	N30	0.8329	30	29.20%
N6	344.93	31	26.80%	N6	0.8129	31	26.80%
N24	337.84	32	24.30%	N27	0.8104	32	21.90%
T9	318.68	33	21.90%	N17	0.8104	33	21.90%
T7	281.94	34	19.50%	N22	0.805	34	19.50%
N30	261.39	35	17.00%	T9	0.7969	35	17.00%
T3	258.33	36	14.60%	T7	0.788	36	14.60%
T8	148.62	37	12.10%	T5	0.7791	37	12.10%
T1	132.06	38	9.70%	N24	0.7716	38	9.70%
T4	96.43	39	7.30%	N10	0.7405	39	7.30%
T5	70.97	40	4.80%	N32	0.704	40	4.80%
N32	67.79	41	2.40%	T10	0.5924	41	2.40%
T10	43.47	42	0.00%	T4	0.5177	42	0.00%

Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distance for ST Honey

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N29	12593.81	1	100.00%	N6	0.9642	1	100.00%
N5	6375.09	2	97.50%	T2	9226	2	97.50%
N23	6014.23	3	95.10%	N10*	0.9219	3	95.10%
N31	5832.96	4	92.60%	N31	0.9203	4	92.60%
N26	5555.79	5	90.20%	N29	0.9194	5	90.20%
N9	4647.56	6	87.80%	N26	0.919	6	87.80%
T2	4354.62	7	85.30%	N5	0.9106	7	85.30%
N11	3749.95	8	82.90%	N17	0.909	8	82.90%
N6	3650.01	9	80.40%	T11	0.9063	9	80.40%
N20	3259.16	10	78.00%	N23	0.9016	10	78.00%
N17	2369.79	11	75.60%	N22*	0.895	11	75.60%
N28	2264.82	12	73.10%	N20	0.89	12	73.10%
N10*	1997.47	13	70.70%	T1	0.8868	13	70.70%
N1	1778.03	14	68.20%	N18	0.8836	14	68.20%
N8	1742.91	15	65.80%	N9	0.881	15	65.80%
N18	1742.85	16	63.40%	N16	0.8804	16	63.40%
N15	1695.26	17	60.90%	N11	0.8777	17	60.90%
N16	1346.31	18	58.50%	N8	0.877	18	58.50%
N22	1207.47	19	56.00%	N15	0.8731	19	56.00%
N30	1074.31	20	53.60%	N28	0.8696	20	53.60%
N3	913.47	21	51.20%	N30	0.8599	21	51.20%
T9	889.88	22	48.70%	N19	0.8373	22	48.70%
N12	868.62	23	46.30%	N24	0.8372	23	46.30%
N13	842.9	24	43.90%	N13	0.8326	24	43.90%
N19	826.82	25	41.40%	N7	0.8323	25	41.40%
N4	818.7	26	39.00%	N21	0.8225	26	39.00%
N27	761.42	27	36.50%	N12	0.8156	27	36.50%
N2	700.4	28	34.10%	T9	0.8091	28	34.10%
N7	687.86	29	31.70%	N14	0.8053	29	31.70%
N21	682.05	30	29.20%	N25	0.8041	30	29.20%
N25	587.72	31	26.80%	N4	0.8032	31	26.80%
N24	569.58	32	24.30%	N2	0.8001	32	24.30%
T11	542.8	33	21.90%	N27	0.7924	33	21.90%
N14	510.64	34	19.50%	N3	0.7886	34	19.50%
T1	341.75	35	17.00%	T8	0.7881	35	17.00%
T8	215.54	36	14.60%	N1	0.7825	36	14.60%
T5	177.28	37	12.10%	T3	0.7425	37	12.10%
N32	142.51	38	9.70%	T5	0.742	38	9.70%
T4	92.6	39	7.30%	T10	0.7155	39	7.30%
T3	62.53	40	4.80%	T4	0.7119	40	4.80%
T7	60.66	41	2.40%	N32	0.7013	41	2.40%
T10	11.09	42	0.00%	T7	0.6736	42	0.00%

Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distance for T Honey

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T7	84016	1	100.00%	N23	0.9517	1	100.00%
T2	17337.5	2	97.50%	N6	0.9514	2	97.50%
N29	4120.59	3	95.10%	T11	0.9276	3	95.10%
N23	3493.41	4	92.60%	N8	0.9152	4	92.60%
N31	2661.3	5	90.20%	N22	0.9106	5	90.20%
N5	2235.94	6	87.80%	N10	0.9105	6	87.80%
N6	2188.87	7	85.30%	N5	0.9105	7	85.30%
N26	2043.21	8	82.90%	N18	0.9082	8	82.90%
N9	1883.41	9	80.40%	N9	0.9073	9	80.40%
N20	1156.73	10	78.00%	N26	0.9	10	78.00%
N10	1097.63	11	75.60%	N20	0.899	11	75.60%
N17	1052.48	12	73.10%	N17	0.8975	12	73.10%
T11	1037.43	13	70.70%	N19	0.8973	13	70.70%
N22	1029.37	14	68.20%	T2	0.8937	14	68.20%
N8	1020.89	15	65.80%	N28	0.8861	15	65.80%
N28	1019.52	16	63.40%	N29	0.8825	16	63.40%
N18	900.7	17	60.90%	N15	0.879	17	60.90%
N15	870.4	18	58.50%	T8	0.8762	18	58.50%
N16	802.34	19	56.00%	N16	0.8741	19	56.00%
T9	660.37	20	53.60%	N1	0.8677	20	53.60%
N11	657.82	21	51.20%	N13	0.8668	21	51.20%
N12	554.35	22	48.70%	T1	0.8653	22	48.70%
N13	544	23	46.30%	N7	0.8635	23	46.30%
N27	537.6	24	43.90%	N11	0.8607	24	43.90%
T1	513.37	25	41.40%	N21	0.8592	25	41.40%
N19	475.41	26	39.00%	N2	0.8588	26	39.00%
N7	474.97	27	36.50%	N4	0.8581	27	36.50%
N1	446.23	28	34.10%	N3	0.8504	28	34.10%
N21	440.02	29	31.70%	T9	0.8484	29	31.70%
N14	434.49	30	29.20%	N12	0.8464	30	29.20%
N30	416.91	31	26.80%	N31	0.8442	31	26.80%
N25	321.53	32	24.30%	N14	0.8426	32	24.30%
N3	318.65	33	21.90%	N27	0.8302	33	21.90%
N24	291.55	34	19.50%	N30	0.8077	34	19.50%
N2	274.43	35	17.00%	N25	0.8066	35	17.00%
N4	263.23	36	14.60%	N24	0.8002	36	14.60%
T8	185.14	37	12.10%	T4	0.7996	37	12.10%
N32	143.86	38	9.70%	T5	0.7527	38	9.70%
T3	114.05	39	7.30%	T10	0.7168	39	7.30%
T4	98.99	40	4.80%	N32	0.6727	40	4.80%
T5	90.02	41	2.40%	T3	0.5971	41	2.40%
T10	76.1	42	0.00%	T7	0.5829	42	0.00%

Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distance for T3 Honey

D^2				$D_A{}^2$			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N29	3688.43	1	100.00%	N6	0.9642	1	100.00%
N5	3619.54	2	97.50%	T2	0.9226	2	97.50%
N23	2725.01	3	95.10%	N10	0.9219	3	95.10%
N31	2314.98	4	92.60%	N31	0.9203	4	92.60%
N26	2284.21	5	90.20%	N29	0.9194	5	90.20%
N9	1939.9	6	87.80%	N26	0.919	6	87.80%
N10	1787.67	7	85.30%	N5	0.9106	7	85.30%
N17	1356.67	8	82.90%	N17	0.909	8	82.90%
N20	1260.21	9	80.40%	T11	0.9063	9	80.40%
N6	1076.32	10	78.00%	N23	0.9016	10	78.00%
N8	1056.54	11	75.60%	N22	0.895	11	75.60%
T2	1002.97	12	73.10%	N20	0.89	12	73.10%
N22	986.39	13	70.70%	T1	0.8868	13	70.70%
N15	959.63	14	68.20%	N18	0.8836	14	68.20%
N18	930.71	15	65.80%	N9	0.881	15	65.80%
N16	925.82	16	63.40%	N16	0.8804	16	63.40%
N28	890.07	17	60.90%	N11	0.8777	17	60.90%
N11	716.85	18	58.50%	N8	0.877	18	58.50%
N13	692.65	19	56.00%	N15	0.8731	19	56.00%
T11	685.45	20	53.60%	N28	0.8696	20	53.60%
N21	628.14	21	51.20%	N30	0.8599	21	51.20%
N12	626.89	22	48.70%	N19	0.8373	22	48.70%
N1	573.16	23	46.30%	N24	0.8372	23	46.30%
N7	512.38	24	43.90%	N13	0.8326	24	43.90%
N14	477.42	25	41.40%	N7	0.8323	25	41.40%
N19	411.58	26	39.00%	N21	0.8225	26	39.00%
N4	377.42	27	36.50%	N12	0.8156	27	36.50%
N27	371.13	28	34.10%	T9	0.8091	28	34.10%
N2	350.85	29	31.70%	N14	0.8053	29	31.70%
N25	337.76	30	29.20%	N25	0.8041	30	29.20%
N30	320.51	31	26.80%	N4	0.8032	31	26.80%
N3	300.53	32	24.30%	N2	0.8001	32	24.30%
T1	298.75	33	21.90%	N27	0.7924	33	21.90%
T9	288.86	34	19.50%	N3	0.7886	34	19.50%
N24	210.66	35	17.00%	T8	0.7881	35	17.00%
T3	179.84	36	14.60%	N1	0.7825	36	14.60%
T8	128.25	37	12.10%	T3	0.7425	37	12.10%
N32	97.12	38	9.70%	T5	0.742	38	9.70%
T7	74.44	39	7.30%	T10	0.7155	39	7.30%
T4	58.29	40	4.80%	T4	0.7119	40	4.80%
T5	54.34	41	2.40%	N32	0.7013	41	2.40%
T10	52.63	42	0.00%	T7	0.6736	42	0.00%

Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distance for TK Honey

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N23	2663.26	1	100.00%	N5	0.9366	1	100.00%
N29	2538.28	2	97.50%	N23	0.9269	2	97.50%
N5	2069.87	3	95.10%	T11	0.9262	3	95.10%
N9	2066.03	4	92.60%	N6	0.9207	4	92.60%
N26	2050.25	5	90.20%	N10	0.9166	5	90.20%
N20	1580.12	6	87.80%	N11	0.895	6	87.80%
N17	1568.36	7	85.30%	N17	0.8876	7	85.30%
N31	1553.67	8	82.90%	N29	0.8851	8	82.90%
N16	1230.39	9	80.40%	N22	0.8844	9	80.40%
N10	1189.51	10	78.00%	N18	0.8678	10	78.00%
N15	1095.07	11	75.60%	T2	0.8665	11	75.60%
N13	1062.34	12	73.10%	N15	0.8644	12	73.10%
N18	1005.69	13	70.70%	N16	0.8618	13	70.70%
N6	977.35	14	68.20%	N19	0.8608	14	68.20%
N8	916.76	15	65.80%	N12	0.8595	15	65.80%
N22	865.9	16	63.40%	T1	0.8587	16	63.40%
T11	862.7	17	60.90%	N8	0.8579	17	60.90%
N21	860.6	18	58.50%	N26	0.8507	18	58.50%
N11	840.33	19	56.00%	T8	0.8479	19	56.00%
N28	786.16	20	53.60%	N20	0.8475	20	53.60%
N12	775.97	21	51.20%	N29	0.8462	21	51.20%
T2	749.26	22	48.70%	N13	0.8439	22	48.70%
N7	685.13	23	46.30%	N25	0.8296	23	46.30%
N14	540.21	24	43.90%	N28	0.8207	24	43.90%
N1	526.24	25	41.40%	N14	0.816	25	41.40%
N25	434.22	26	39.00%	T9	0.8112	26	39.00%
N19	424.72	27	36.50%	N1	0.8102	27	36.50%
N3	396.13	28	34.10%	N7	0.81	28	34.10%
N4	360.71	29	31.70%	N21	0.8082	29	31.70%
N27	343.16	30	29.20%	N4	0.8041	30	29.20%
N2	325.63	31	26.80%	N31	0.8022	31	26.80%
T9	316.08	32	24.30%	N2	0.7969	32	24.30%
N30	266.31	33	21.90%	N27	0.7815	33	21.90%
T1	205.23	34	19.50%	N31	0.7576	34	19.50%
N24	175.27	35	17.00%	N24	0.7345	35	17.00%
T8	159.03	36	14.60%	T5	0.7164	36	14.60%
T7	121.11	37	12.10%	T10	0.7095	37	12.10%
N32	106.62	38	9.70%	T4	0.6858	38	9.70%
T10	99.81	39	7.30%	T7	0.6042	39	7.30%
T5	65.49	40	4.80%	T3	0.5951	40	4.80%
T4	45.26	41	2.40%	N30	0.5621	41	2.40%
T3	26.77	42	0.00%	N32	0.5095	42	0.00%

Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distance for TLH Honey

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N29	2865.03	1	100.00%	N6	0.9391	1	100.00%
N9	2833.27	2	97.50%	N20	0.9362	2	97.50%
N26	2526.77	3	95.10%	N9	0.9353	3	95.10%
N17	2326.74	4	92.60%	N18	0.9259	4	92.60%
N10	2151.57	5	90.20%	N22	0.9239	5	90.20%
N5	1997.04	6	87.80%	N8	0.9195	6	87.80%
N20	1986.03	7	85.30%	N26	0.9189	7	85.30%
N31	1898.18	8	82.90%	T11	0.9161	8	82.90%
N18	1889.85	9	80.40%	N28	0.9108	9	80.40%
N15	1711.96	10	78.00%	N7*	0.9087	10	78.00%
N8	1539.02	11	75.60%	N17	0.9079	11	75.60%
N22	1457.59	12	73.10%	N15*	0.905	12	73.10%
N16	1416.93	13	70.70%	N21	0.9036	13	70.70%
N23	1328.33	14	68.20%	N31	0.9032	14	68.20%
N12	1292.17	15	65.80%	N5	0.8974	15	65.80%
N13	1139.75	16	63.40%	N30	0.8969	16	63.40%
N28	1069.02	17	60.90%	N13	0.896	17	60.90%
N21	992.47	18	58.50%	N23	0.8954	18	58.50%
N27	959.76	19	56.00%	N27	0.8952	19	56.00%
N7	926.02	20	53.60%	N10	0.8944	20	53.60%
N11	900.11	21	51.20%	N12	0.8926	21	51.20%
T11	868.3	22	48.70%	N1	0.8916	22	48.70%
N1	851.84	23	46.30%	N29	0.8852	23	46.30%
N19	772.37	24	43.90%	N3	0.8846	24	43.90%
N3	751.01	25	41.40%	N19	0.8827	25	41.40%
N6	698.65	26	39.00%	N11	0.8798	26	39.00%
N25	664.92	27	36.50%	N2	0.8792	27	36.50%
N14	632.77	28	34.10%	N25	0.8678	28	34.10%
N2	578.12	29	31.70%	N16	0.8644	29	31.70%
T2	428.15	30	29.20%	N14	0.8631	30	29.20%
N4	422.11	31	26.80%	N4	0.8435	31	26.80%
T10	419.94	32	24.30%	T2	0.8404	32	24.30%
N24	378.11	33	21.90%	N24	0.8121	33	21.90%
N30	345.88	34	19.50%	T1	0.7814	34	19.50%
T5	201.75	35	17.00%	T8	0.7734	35	17.00%
T9	148.68	36	14.60%	T10	0.7712	36	14.60%
N32	98.14	37	12.10%	T5	0.7628	37	12.10%
T1	94.16	38	9.70%	N32	0.7611	38	9.70%
T8	79.59	39	7.30%	T7	0.6885	39	7.30%
T7	77.88	40	4.80%	T9	0.6707	40	4.80%
T4	27.32	41	2.40%	T3	0.6143	41	2.40%
T3	24.61	42	0.00%	T4	0.6131	42	0.00%

Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distance for TN Honey

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T3	5306	1	100.00%	N22	0.9255	1	100.00%
N23	3747.14	2	97.50%	T11	0.9229	2	97.50%
N29	2640.31	3	95.10%	N29	0.9216	3	95.10%
N5	2182.42	4	92.60%	N10	0.9156	4	92.60%
N9	2025	5	90.20%	N26	0.9137	5	90.20%
N26	1770.22	6	87.80%	N5	0.9082	6	87.80%
N31	1473.64	7	85.30%	N17	0.9033	7	85.30%
N20	1411.19	8	82.90%	N18	0.8995	8	82.90%
N10	1326	9	80.40%	N19	0.8956	9	80.40%
N6	1209.44	10	78.00%	N9	0.8902	10	78.00%
N8	1206.69	11	75.60%	T2	0.887	11	75.60%
T11	1153.05	12	73.10%	N28	0.8814	12	73.10%
N22	1134.53	13	70.70%	N6	0.8779	13	70.70%
N17	1110.75	14	68.20%	N20	0.8706	14	68.20%
N18	1110.75	15	65.80%	N31	0.8698	15	65.80%
N11	1108.25	16	63.40%	N21	0.8694	16	63.40%
N15	1016.42	17	60.90%	N16	0.8664	17	60.90%
N1	913.06	18	58.50%	N12	0.8648	18	58.50%
N13	901.48	19	56.00%	N7	0.8647	19	56.00%
N16	896.82	20	53.60%	N23	0.8644	20	53.60%
N12	800.97	21	51.20%	N27	0.863	21	51.20%
N28	790.66	22	48.70%	N15	0.8628	22	48.70%
N3	782.48	23	46.30%	N8	0.8603	23	46.30%
N21	692.11	24	43.90%	N2	0.8553	24	43.90%
N7	646.58	25	41.40%	N3	0.8544	25	41.40%
N27	628.73	26	39.00%	N1	0.8528	26	39.00%
N25	609.36	27	36.50%	N30	0.8527	27	36.50%
N2	595.51	28	34.10%	N25	0.8475	28	34.10%
N19	573.71	29	31.70%	N14	0.8446	29	31.70%
N4	544.58	30	29.20%	N13	0.8438	30	29.20%
N14	530.46	31	26.80%	N4	0.8262	31	26.80%
T2	492.3	32	24.30%	T1	0.8181	32	24.30%
N24	331.69	33	21.90%	N11	0.8163	33	21.90%
N30	257.81	34	19.50%	N24	0.7868	34	19.50%
T1	142.21	35	17.00%	N32	0.7464	35	17.00%
T7	115.22	36	14.60%	T7	0.7394	36	14.60%
N32	107.78	37	12.10%	T8	0.7383	37	12.10%
T8	100.75	38	9.70%	T9	0.7261	38	9.70%
T10	89.38	39	7.30%	T3	0.7189	39	7.30%
T5	62.51	40	4.80%	T5	0.706	40	4.80%
T4	46.21	41	2.40%	T10	0.6816	41	2.40%
T9	42.27	42	0.00%	T4	0.6441	42	0.00%

Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distance for WT Honey

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N5	4127.81	1	100.00%	N23	0.9408	1	100.00%
N29	4037.63	2	97.50%	N28	0.9369	2	97.50%
N23	3405.52	3	95.10%	N20	0.9356	3	95.10%
N26	3347.08	4	92.60%	N31	0.9352	4	92.60%
N9	2942.97	5	90.20%	N6	0.9344	5	90.20%
N20	2461.75	6	87.80%	N26	0.9315	6	87.80%
N31	2299.67	7	85.30%	N5	0.9306	7	85.30%
N6	2016.16	8	82.90%	N10	0.9272	8	82.90%
N11	1739.11	9	80.40%	N29	0.9247	9	80.40%
N17	1666.27	10	78.00%	N9	0.9199	10	78.00%
N28	1488.67	11	75.60%	N22	0.914	11	75.60%
N10	1444.13	12	73.10%	N8	0.9127	12	73.10%
N15	1443.47	13	70.70%	N15	0.9104	13	70.70%
N8	1416.52	14	68.20%	N16	0.9085	14	68.20%
N16	1315.33	15	65.80%	N11	0.9052	15	65.80%
N18	1259.19	16	63.40%	N27	0.9038	16	63.40%
T11	1070.54	17	60.90%	N25	0.9016	17	60.90%
T2	1016.2	18	58.50%	N12	0.9006	18	58.50%
N12	1012.62	19	56.00%	N31	0.8956	19	56.00%
N1	899.3	20	53.60%	N18	0.8947	20	53.60%
N22	881.08	21	51.20%	T11	0.8947	21	51.20%
N3	834.49	22	48.70%	N17	0.8915	22	48.70%
N13	831.93	23	46.30%	N1	0.8898	23	46.30%
N7	809.65	24	43.90%	N30	0.8803	24	43.90%
N27	732.23	25	41.40%	N14	0.8796	25	41.40%
N30	723.78	26	39.00%	N4	0.8778	26	39.00%
N21	719.4	27	36.50%	N7	0.8732	27	36.50%
N4	668.77	28	34.10%	N2	0.8725	28	34.10%
N19	631.36	29	31.70%	N13	0.8683	29	31.70%
N14	588.74	30	29.20%	N19	0.8616	30	29.20%
N2	542.75	31	26.80%	N21	0.8595	31	26.80%
N25	471.72	32	24.30%	T2	0.8198	32	24.30%
T10	374.6	33	21.90%	N24	0.8061	33	21.90%
N24	296.97	34	19.50%	T10	0.7894	34	19.50%
T7	263	35	17.00%	T1	0.778	35	17.00%
N32	154.08	36	14.60%	T8	0.777	36	14.60%
T1	132.66	37	12.10%	T9	0.763	37	12.10%
T3	104.01	38	9.70%	N32	0.7011	38	9.70%
T5	70.1	39	7.30%	T5	0.6943	39	7.30%
T8	63.53	40	4.80%	T3	0.6848	40	4.80%
T4	43.16	41	2.40%	T4	0.6747	41	2.40%
T9	36.63	42	0.00%	T7	0.6743	42	0.00%

Results of Fused Feature Ranking for LLDF based on Bounded and Unbounded Mahalanobis Distance for YB Honey

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N5	6474	1	100.00%	N11	0.9467	1	100.00%
N23	5287.73	2	97.50%	N28	0.9459	2	97.50%
N29	4512.24	3	95.10%	N9	0.9406	3	95.10%
N26	3137.66	4	92.60%	N26	0.9354	4	92.60%
N6	3085.16	5	90.20%	N20	0.9296	5	90.20%
N9	2511.35	6	87.80%	N6	0.9218	6	87.80%
N31	2324.08	7	85.30%	N23	0.9216	7	85.30%
N20	1784.21	8	82.90%	N17	0.9216	8	82.90%
N11	1685.89	9	80.40%	N5	0.921	9	80.40%
N17	1329.32	10	78.00%	T11	0.9134	10	78.00%
N28	1278.17	11	75.60%	N25	0.911	11	75.60%
N8	1072.09	12	73.10%	N10	0.9088	12	73.10%
N10	1015.58	13	70.70%	N8	0.9075	13	70.70%
T11	960.45	14	68.20%	N18	0.9061	14	68.20%
N16	941.06	15	65.80%	N15	0.904	15	65.80%
N22	915.22	16	63.40%	N27	0.8891	16	63.40%
N15	889.7	17	60.90%	N12	0.8866	17	60.90%
N18	880.81	18	58.50%	N30	0.8852	18	58.50%
N30	856.89	19	56.00%	N16	0.8807	19	56.00%
N21	689.68	20	53.60%	N13	0.8799	20	53.60%
N13	679.78	21	51.20%	N7	0.8794	21	51.20%
N12	639.55	22	48.70%	N22	0.8742	22	48.70%
N7	517.44	23	46.30%	N14	0.8728	23	46.30%
N4	493.31	24	43.90%	N19	0.8703	24	43.90%
N1	484.69	25	41.40%	N21	0.8695	25	41.40%
N14	461.52	26	39.00%	N1	0.8686	26	39.00%
N25	447.94	27	36.50%	N31	0.8682	27	36.50%
N27	399.56	28	34.10%	N29	0.8596	28	34.10%
N3	369.81	29	31.70%	N4	0.8577	29	31.70%
N19	339.41	30	29.20%	N3	0.848	30	29.20%
N2	313.8	31	26.80%	N2	0.8372	31	26.80%
T2	218.66	32	24.30%	T1	0.8312	32	24.30%
N24	209.73	33	21.90%	N24	0.8243	33	21.90%
T1	202.2	34	19.50%	T2	0.8204	34	19.50%
T10	164.84	35	17.00%	N32	0.7648	35	17.00%
N32	108.32	36	14.60%	T9	0.7566	36	14.60%
T7	85.19	37	12.10%	T10	0.7477	37	12.10%
T3	57.36	38	9.70%	T8	0.7058	38	9.70%
T8	46.07	39	7.30%	T7	0.6164	39	7.30%
T9	37.04	40	4.80%	T3	0.6067	40	4.80%
T5	32.67	41	2.40%	T4	0.6042	41	2.40%
T4	22.2	42	0.00%	T5	0.5806	42	0.00%

Appendix C

Results of Single Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distances

Results of Single Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-nose (AS honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N26	1,937.62	1	100.00%	N15	0.9326	1	100.00%
N5	1,872.11	2	96.70%	N5	0.9285	2	96.70%
N29	1,815.44	3	93.50%	N23	0.9214	3	93.50%
N31	1,116.44	4	90.30%	N11	0.9181	4	90.30%
N15	1,086.90	5	87.00%	N29	0.914	5	87.00%
N9	1,058.89	6	83.80%	N26	0.91	6	83.80%
N20	994.57	7	80.60%	N8	0.9099	7	80.60%
N16	928.61	8	77.40%	N18	0.9077	8	77.40%
N23	917.45	9	74.10%	N20	0.8984	9	74.10%
N17	886.27	10	70.90%	N2	0.8969	10	70.90%
N13	832.86	11	67.70%	N4	0.8965	11	67.70%
N8	800.05	12	64.50%	N1	0.8916	12	64.50%
N21	779.23	13	61.20%	N3	0.8907	13	61.20%
N11	755.48	14	58.00%	N16	0.8883	14	58.00%
N18	727.66	15	54.80%	N31	0.8874	15	54.80%
N28	712.29	16	51.60%	N21	0.8834	16	51.60%
N7	626.57	17	48.30%	N9	0.882	17	48.30%
N12	616.34	18	45.10%	N19	0.8743	18	45.10%
N10	582.97	19	41.90%	N12	0.8726	19	41.90%
N1	580.04	20	38.70%	N13	0.8726	20	38.70%
N3	545.42	21	35.40%	N14	0.8722	21	35.40%
N4	516.91	22	32.20%	N28	0.8555	22	32.20%
N14	502.47	23	29.00%	N25	0.8487	23	29.00%
N2	436.33	24	25.80%	N7	0.848	24	25.80%
N22	423.87	25	22.50%	N30	0.8329	25	22.50%
N25	405.44	26	19.30%	N6	0.8129	26	19.30%
N19	385.80	27	16.10%	N17	0.8104	27	16.10%
N27	347.33	28	12.90%	N27	0.8104	28	12.90%
N6	344.93	29	9.60%	N22	0.805	29	9.60%
N24	337.84	30	6.40%	N24	0.7716	30	6.40%
N30	261.39	31	3.20%	N10	0.7405	31	3.20%
N32	67.79	32	0.00%	N32	0.704	32	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-tongue (AS honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T11	888.82	1	100.00%	T11	0.8963	1	100.00%
T2	498.87	2	88.80%	T2	0.8751	2	88.80%
T9	318.68	3	77.70%	T1	0.8386	3	77.70%
T7	281.94	4	66.60%	T3	0.8383	4	66.60%
T3	258.33	5	55.50%	T8	0.8379	5	55.50%
T8	148.62	6	44.40%	T9	0.7969	6	44.40%
T1	132.06	7	33.30%	T7	0.788	7	33.30%
T4	96.43	8	22.20%	T5	0.7791	8	22.20%
T5	70.97	9	11.10%	T10	0.5924	9	11.10%
T10	43.47	10	0.00%	T4	0.5177	10	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-nose (ST honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N29	12,593.81	1	100.00%	N6	0.9642	1	100.00%
N5	6,375.09	2	96.70%	N10*	0.9219	2	96.70%
N23	6,014.23	3	93.50%	N31	0.9203	3	93.50%
N31	5,832.96	4	90.30%	N29	0.9194	4	90.30%
N26	5,555.79	5	87.00%	N26	0.919	5	87.00%
N9	4,647.56	6	83.80%	N5	0.9106	6	83.80%
N11	3,749.95	7	80.60%	N17	0.909	7	80.60%
N6	3,650.01	8	77.40%	N23	0.9016	8	77.40%
N20	3,259.16	9	74.10%	N22	0.895	9	74.10%
N17	2,369.79	10	70.90%	N20	0.89	10	70.90%
N28	2,264.82	11	67.70%	N18	0.8836	11	67.70%
N10	1,997.47	12	64.50%	N9	0.881	12	64.50%
N1	1,778.03	13	61.20%	N16	0.8804	13	61.20%
N8	1,742.91	14	58.00%	N11	0.8777	14	58.00%
N18	1,742.85	15	54.80%	N8	0.877	15	54.80%
N15	1,695.26	16	51.60%	N15	0.8731	16	51.60%
N16	1,346.31	17	48.30%	N28	0.8696	17	48.30%
N22	1,207.47	18	45.10%	N30	0.8599	18	45.10%
N30	1,074.31	19	41.90%	N19	0.8373	19	41.90%
N3	913.47	20	38.70%	N24	0.8372	20	38.70%
N12	868.62	21	35.40%	N13	0.8326	21	35.40%
N13	842.90	22	32.20%	N7	0.8323	22	32.20%
N19	826.82	23	29.00%	N21	0.8225	23	29.00%
N4	818.70	24	25.80%	N12	0.8156	24	25.80%
N27	761.42	25	22.50%	N14	0.8053	25	22.50%
N2	700.40	26	19.30%	N25	0.8041	26	19.30%
N7	687.86	27	16.10%	N4	0.8032	27	16.10%
N21	682.05	28	12.90%	N2	0.8001	28	12.90%
N25	587.72	29	9.60%	N27	0.7924	29	9.60%
N24	569.58	30	6.40%	N3	0.7886	30	6.40%
N14	510.64	31	3.20%	N1	0.7825	31	3.20%
N32	142.51	32	0.00%	N32	0.7013	32	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-tongue (ST honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T2	4,354.62	1	100.00%	T2	9226	1	100.00%
T9	889.88	2	88.80%	T11	0.9063	2	88.80%
T11	542.80	3	77.70%	T1	0.8868	3	77.70%
T1	341.75	4	66.60%	T9	0.8091	4	66.60%
T8	215.54	5	55.50%	T8	0.7881	5	55.50%
T5	177.28	6	44.40%	T3	0.7425	6	44.40%
T4	92.60	7	33.30%	T5	0.742	7	33.30%
T3	62.53	8	22.20%	T10	0.7155	8	22.20%
T7	60.66	9	11.10%	T4	0.7119	9	11.10%
T10	11.09	10	0.00%	T7	0.6736	10	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-nose (T honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N29	4,120.59	1	100.00%	N23	0.9517	1	100.00%
N23	3,493.41	2	96.70%	N6	0.9514	2	96.70%
N31	2,661.30	3	93.50%	N8	0.9152	3	93.50%
N5	2,235.94	4	90.30%	N22	0.9106	4	90.30%
N6	2,188.87	5	87.00%	N10	0.9105	5	87.00%
N26	2,043.21	6	83.80%	N5	0.9105	6	83.80%
N9	1,883.41	7	80.60%	N18	0.9082	7	80.60%
N20	1,156.73	8	77.40%	N9	0.9073	8	77.40%
N10	1,097.63	9	74.10%	N26	0.9	9	74.10%
N17	1,052.48	10	70.90%	N20	0.899	10	70.90%
N22	1,029.37	11	67.70%	N17	0.8975	11	67.70%
N8	1,020.89	12	64.50%	N19	0.8973	12	64.50%
N28	1,019.52	13	61.20%	N28	0.8861	13	61.20%
N18	900.70	14	58.00%	N29	0.8825	14	58.00%
N15	870.40	15	54.80%	N15	0.879	15	54.80%
N16	802.34	16	51.60%	N16	0.8741	16	51.60%
N11	657.82	17	48.30%	N1	0.8677	17	48.30%
N12	554.35	18	45.10%	N13	0.8668	18	45.10%
N13	544.00	19	41.90%	N7	0.8635	19	41.90%
N27	537.60	20	38.70%	N11	0.8607	20	38.70%
N19	475.41	21	35.40%	N21	0.8592	21	35.40%
N7	474.97	22	32.20%	N2	0.8588	22	32.20%
N1	446.23	23	29.00%	N4	0.8581	23	29.00%
N21	440.02	24	25.80%	N3	0.8504	24	25.80%
N14	434.49	25	22.50%	N12	0.8464	25	22.50%
N30	416.91	26	19.30%	N31	0.8442	26	19.30%
N25	321.53	27	16.10%	N14	0.8426	27	16.10%
N3	318.65	28	12.90%	N27	0.8302	28	12.90%
N24	291.55	29	9.60%	N30	0.8077	29	9.60%
N2	274.43	30	6.40%	N25	0.8066	30	6.40%
N4	263.23	31	3.20%	N24	0.8002	31	3.20%
N32	143.86	32	0.00%	N32	0.6727	32	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-tongue (T honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T7	84,016.00	1	100.00%	T11	0.9276	1	100.00%
T2	17,337.50	2	88.80%	T2	0.8937	2	88.80%
T11	1,037.43	3	77.70%	T8	0.8762	3	77.70%
T9	660.37	4	66.60%	T1	0.8653	4	66.60%
T1	513.37	5	55.50%	T9	0.8484	5	55.50%
T8	185.14	6	44.40%	T4	0.7996	6	44.40%
T3	114.05	7	33.30%	T5	0.7527	7	33.30%
T4	98.99	8	22.20%	T10	0.7168	8	22.20%
T5	90.02	9	11.10%	T3	0.5971	9	11.10%
T10	76.10	10	0.00%	T7	0.5829	10	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-nose (T3 honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N29	3,688.43	1	100.00%	N6	0.9642	1	100.00%
N5	3,619.54	2	96.70%	N10	0.9219	2	96.70%
N23	2,725.01	3	93.50%	N31	0.9203	3	93.50%
N31	2,314.98	4	90.30%	N29	0.9194	4	90.30%
N26	2,284.21	5	87.00%	N26	0.919	5	87.00%
N9	1,939.90	6	83.80%	N5	0.9106	6	83.80%
N10	1,787.67	7	80.60%	N17	0.909	7	80.60%
N17	1,356.67	8	77.40%	N23	0.9016	8	77.40%
N20	1,260.21	9	74.10%	N22	0.895	9	74.10%
N6	1,076.32	10	70.90%	N20	0.89	10	70.90%
N8	1,056.54	11	67.70%	N18	0.8836	11	67.70%
N22	986.39	12	64.50%	N9	0.881	12	64.50%
N15	959.63	13	61.20%	N16	0.8804	13	61.20%
N18	930.71	14	58.00%	N11	0.8777	14	58.00%
N16	925.82	15	54.80%	N8	0.877	15	54.80%
N28	890.07	16	51.60%	N15	0.8731	16	51.60%
N11	716.85	17	48.30%	N28	0.8696	17	48.30%
N13	692.65	18	45.10%	N30	0.8599	18	45.10%
N21	628.14	19	41.90%	N19	0.8373	19	41.90%
N12	626.89	20	38.70%	N24	0.8372	20	38.70%
N1	573.16	21	35.40%	N13	0.8326	21	35.40%
N7	512.38	22	32.20%	N7	0.8323	22	32.20%
N14	477.42	23	29.00%	N21	0.8225	23	29.00%
N19	411.58	24	25.80%	N12	0.8156	24	25.80%
N4	377.42	25	22.50%	N14	0.8053	25	22.50%
N27	371.13	26	19.30%	N25	0.8041	26	19.30%
N2	350.85	27	16.10%	N4	0.8032	27	16.10%
N25	337.76	28	12.90%	N2	0.8001	28	12.90%
N30	320.51	29	9.60%	N27	0.7924	29	9.60%
N3	300.53	30	6.40%	N3	0.7886	30	6.40%
N24	210.66	31	3.20%	N1	0.7825	31	3.20%
N32	97.12	32	0.00%	N32	0.7013	32	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-tongue (T3 honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T2	1,002.97	1	100.00%	T2	0.9226	1	100.00%
T11	685.45	2	88.80%	T11	0.9063	2	88.80%
T1	298.75	3	77.70%	T1	0.8868	3	77.70%
T9	288.86	4	66.60%	T9	0.8091	4	66.60%
T3	179.84	5	55.50%	T8	0.7881	5	55.50%
T8	128.25	6	44.40%	T3	0.7425	6	44.40%
T7	74.44	7	33.30%	T5	0.742	7	33.30%
T4	58.29	8	22.20%	T10	0.7155	8	22.20%
T5	54.34	9	11.10%	T4	0.7119	9	11.10%
T10	52.63	10	0.00%	T7	0.6736	10	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-nose (TK honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N23	2,663.26	1	100.00%	N5	0.9366	1	100.00%
N29	2,538.28	2	96.70%	N23	0.9269	2	96.70%
N5	2,069.87	3	93.50%	N6	0.9207	3	93.50%
N9	2,066.03	4	90.30%	N10	0.9166	4	90.30%
N26	2,050.25	5	87.00%	N11	0.895	5	87.00%
N20	1,580.12	6	83.80%	N17	0.8876	6	83.80%
N17	1,568.36	7	80.60%	N29	0.8851	7	80.60%
N31	1,553.67	8	77.40%	N22	0.8844	8	77.40%
N16	1,230.39	9	74.10%	N18	0.8678	9	74.10%
N10	1,189.51	10	70.90%	N15	0.8644	10	70.90%
N15	1,095.07	11	67.70%	N16	0.8618	11	67.70%
N13	1,062.34	12	64.50%	N19	0.8608	12	64.50%
N18	1,005.69	13	61.20%	N12	0.8595	13	61.20%
N6	977.35	14	58.00%	N8	0.8579	14	58.00%
N8	916.76	15	54.80%	N26	0.8507	15	54.80%
N22	865.90	16	51.60%	N20	0.8475	16	51.60%
N21	860.60	17	48.30%	N29	0.8462	17	48.30%
N11	840.33	18	45.10%	N13	0.8439	18	45.10%
N28	786.16	19	41.90%	N25	0.8296	19	41.90%
N12	775.97	20	38.70%	N28	0.8207	20	38.70%
N7	685.13	21	35.40%	N14	0.816	21	35.40%
N14	540.21	22	32.20%	N1	0.8102	22	32.20%
N1	526.24	23	29.00%	N7	0.81	23	29.00%
N25	434.22	24	25.80%	N21	0.8082	24	25.80%
N19	424.72	25	22.50%	N4	0.8041	25	22.50%
N3	396.13	26	19.30%	N31	0.8022	26	19.30%
N4	360.71	27	16.10%	N2	0.7969	27	16.10%
N27	343.16	28	12.90%	N27	0.7815	28	12.90%
N2	325.63	29	9.60%	N31	0.7576	29	9.60%
N30	266.31	30	6.40%	N24	0.7345	30	6.40%
N24	175.27	31	3.20%	N30	0.5621	31	3.20%
N32	106.62	32	0.00%	N32	0.5095	32	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-tongue (TK honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T11	862.70	1	100.00%	T11	0.9262	1	100.00%
T2	749.26	2	88.80%	T2	0.8665	2	88.80%
T9	316.08	3	77.70%	T1	0.8587	3	77.70%
T1	205.23	4	66.60%	T8	0.8479	4	66.60%
T8	159.03	5	55.50%	T9	0.8112	5	55.50%
T7	121.11	6	44.40%	T5	0.7164	6	44.40%
T10	99.81	7	33.30%	T10	0.7095	7	33.30%
T5	65.49	8	22.20%	T4	0.6858	8	22.20%
T4	45.26	9	11.10%	T7	0.6042	9	11.10%
T3	26.77	10	0.00%	T3	0.5951	10	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-nose (TLH honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N29	2,865.03	1	100.00%	N6	0.9391	1	100.00%
N9	2,833.27	2	96.70%	N20	0.9362	2	96.70%
N26	2,526.77	3	93.50%	N9	0.9353	3	93.50%
N17	2,326.74	4	90.30%	N18	0.9259	4	90.30%
N10	2,151.57	5	87.00%	N22	0.9239	5	87.00%
N5	1,997.04	6	83.80%	N8	0.9195	6	83.80%
N20	1,986.03	7	80.60%	N26	0.9189	7	80.60%
N31	1,898.18	8	77.40%	N28	0.9108	8	77.40%
N18	1,889.85	9	74.10%	N7	0.9087	9	74.10%
N15	1,711.96	10	70.90%	N17	0.9079	10	70.90%
N8	1,539.02	11	67.70%	N15	0.905	11	67.70%
N22	1,457.59	12	64.50%	N21	0.9036	12	64.50%
N16	1,416.93	13	61.20%	N31	0.9032	13	61.20%
N23	1,328.33	14	58.00%	N5	0.8974	14	58.00%
N12	1,292.17	15	54.80%	N30	0.8969	15	54.80%
N13	1,139.75	16	51.60%	N13	0.896	16	51.60%
N28	1,069.02	17	48.30%	N23	0.8954	17	48.30%
N21	992.47	18	45.10%	N27	0.8952	18	45.10%
N27	959.76	19	41.90%	N10	0.8944	19	41.90%
N7	926.02	20	38.70%	N12	0.8926	20	38.70%
N11	900.11	21	35.40%	N1	0.8916	21	35.40%
N1	851.84	22	32.20%	N29	0.8852	22	32.20%
N19	772.37	23	29.00%	N3	0.8846	23	29.00%
N3	751.01	24	25.80%	N19	0.8827	24	25.80%
N6	698.65	25	22.50%	N11	0.8798	25	22.50%
N25	664.92	26	19.30%	N2	0.8792	26	19.30%
N14	632.77	27	16.10%	N25	0.8678	27	16.10%
N2	578.12	28	12.90%	N16	0.8644	28	12.90%
N4	422.11	29	9.60%	N14	0.8631	29	9.60%
N24	378.11	30	6.40%	N4	0.8435	30	6.40%
N30	345.88	31	3.20%	N24	0.8121	31	3.20%
N32	98.14	32	0.00%	N32	0.7611	32	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-tongue (TLH honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T11	868.30	1	100.00%	T11	0.9161	1	100.00%
T2	428.15	2	88.80%	T2	0.8404	2	88.80%
T10	419.94	3	77.70%	T1	0.7814	3	77.70%
T5	201.75	4	66.60%	T8	0.7734	4	66.60%
T9	148.68	5	55.50%	T10	0.7712	5	55.50%
T1	94.16	6	44.40%	T5	0.7628	6	44.40%
T8	79.59	7	33.30%	T7	0.6885	7	33.30%
T7	77.88	8	22.20%	T9	0.6707	8	22.20%
T4	27.32	9	11.10%	T3	0.6143	9	11.10%
T3	24.61	10	0.00%	T4	0.6131	10	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-nose (TN honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N23	3,747.14	1	100.00%	N22	0.9255	1	100.00%
N29	2,640.31	2	96.70%	N29	0.9216	2	96.70%
N5	2,182.42	3	93.50%	N10	0.9156	3	93.50%
N9	2,025.00	4	90.30%	N26	0.9137	4	90.30%
N26	1,770.22	5	87.00%	N5	0.9082	5	87.00%
N31	1,473.64	6	83.80%	N17	0.9033	6	83.80%
N20	1,411.19	7	80.60%	N18	0.8995	7	80.60%
N10	1,326.00	8	77.40%	N19	0.8956	8	77.40%
N6	1,209.44	9	74.10%	N9	0.8902	9	74.10%
N8	1,206.69	10	70.90%	N28	0.8814	10	70.90%
N22	1,134.53	11	67.70%	N6	0.8779	11	67.70%
N17	1,110.75	12	64.50%	N20	0.8706	12	64.50%
N18	1,110.75	13	61.20%	N31	0.8698	13	61.20%
N11	1,108.25	14	58.00%	N21	0.8694	14	58.00%
N15	1,016.42	15	54.80%	N16	0.8664	15	54.80%
N1	913.06	16	51.60%	N12	0.8648	16	51.60%
N13	901.48	17	48.30%	N7	0.8647	17	48.30%
N16	896.82	18	45.10%	N23	0.8644	18	45.10%
N12	800.97	19	41.90%	N27	0.863	19	41.90%
N28	790.66	20	38.70%	N15	0.8628	20	38.70%
N3	782.48	21	35.40%	N8	0.8603	21	35.40%
N21	692.11	22	32.20%	N2	0.8553	22	32.20%
N7	646.58	23	29.00%	N3	0.8544	23	29.00%
N27	628.73	24	25.80%	N1	0.8528	24	25.80%
N25	609.36	25	22.50%	N30	0.8527	25	22.50%
N2	595.51	26	19.30%	N25	0.8475	26	19.30%
N19	573.71	27	16.10%	N14	0.8446	27	16.10%
N4	544.58	28	12.90%	N13	0.8438	28	12.90%
N14	530.46	29	9.60%	N4	0.8262	29	9.60%
N24	331.69	30	6.40%	N11	0.8163	30	6.40%
N30	257.81	31	3.20%	N24	0.7868	31	3.20%
N32	107.78	32	0.00%	N32	0.7464	32	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-tongue (TN honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T3	5,306.00	1	100.00%	T11	0.9229	1	100.00%
T11	1,153.05	2	88.80%	T2	0.887	2	88.80%
T2	492.30	3	77.70%	T1	0.8181	3	77.70%
T1	142.21	4	66.60%	T7	0.7394	4	66.60%
T7	115.22	5	55.50%	T8	0.7383	5	55.50%
T8	100.75	6	44.40%	T9	0.7261	6	44.40%
T10	89.38	7	33.30%	T3	0.7189	7	33.30%
T5	62.51	8	22.20%	T5	0.706	8	22.20%
T4	46.21	9	11.10%	T10	0.6816	9	11.10%
T9	42.27	10	0.00%	T4	0.6441	10	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-nose (WT honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N5	4,127.81	1	100.00%	N23	0.9408	1	100.00%
N29	4,037.63	2	96.70%	N28	0.9369	2	96.70%
N23	3,405.52	3	93.50%	N20	0.9356	3	93.50%
N26	3,347.08	4	90.30%	N31	0.9352	4	90.30%
N9	2,942.97	5	87.00%	N6	0.9344	5	87.00%
N20	2,461.75	6	83.80%	N26	0.9315	6	83.80%
N31	2,299.67	7	80.60%	N5	0.9306	7	80.60%
N6	2,016.16	8	77.40%	N10	0.9272	8	77.40%
N11	1,739.11	9	74.10%	N29	0.9247	9	74.10%
N17	1,666.27	10	70.90%	N9	0.9199	10	70.90%
N28	1,488.67	11	67.70%	N22	0.914	11	67.70%
N10	1,444.13	12	64.50%	N8	0.9127	12	64.50%
N15	1,443.47	13	61.20%	N15	0.9104	13	61.20%
N8	1,416.52	14	58.00%	N16	0.9085	14	58.00%
N16	1,315.33	15	54.80%	N11	0.9052	15	54.80%
N18	1,259.19	16	51.60%	N27	0.9038	16	51.60%
N12	1,012.62	17	48.30%	N25	0.9016	17	48.30%
N1	899.30	18	45.10%	N12	0.9006	18	45.10%
N22	881.08	19	41.90%	N31	0.8956	19	41.90%
N3	834.49	20	38.70%	N18	0.8947	20	38.70%
N13	831.93	21	35.40%	N17	0.8915	21	35.40%
N7	809.65	22	32.20%	N1	0.8898	22	32.20%
N27	732.23	23	29.00%	N30	0.8803	23	29.00%
N30	723.78	24	25.80%	N14	0.8796	24	25.80%
N21	719.40	25	22.50%	N4	0.8778	25	22.50%
N4	668.77	26	19.30%	N7	0.8732	26	19.30%
N19	631.36	27	16.10%	N2	0.8725	27	16.10%
N14	588.74	28	12.90%	N13	0.8683	28	12.90%
N2	542.75	29	9.60%	N19	0.8616	29	9.60%
N25	471.72	30	6.40%	N21	0.8595	30	6.40%
N24	296.97	31	3.20%	N24	0.8061	31	3.20%
N32	154.08	32	0.00%	N32	0.7011	32	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-tongue (WT honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T11	1,070.54	1	100.00%	T11	0.8947	1	100.00%
T2	1,016.20	2	88.80%	T2	0.8198	2	88.80%
T10	374.60	3	77.70%	T10	0.7894	3	77.70%
T7	263.00	4	66.60%	T1	0.778	4	66.60%
T1	132.66	5	55.50%	T8	0.777	5	55.50%
T3	104.01	6	44.40%	T9	0.763	6	44.40%
T5	70.10	7	33.30%	T5	0.6943	7	33.30%
T8	63.53	8	22.20%	T3	0.6848	8	22.20%
T4	43.16	9	11.10%	T4	0.6747	9	11.10%
T9	36.63	10	0.00%	T7	0.6743	10	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-nose (YB honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
N5	6,474.00	1	100.00%	N11	0.9467	1	100.00%
N23	5,287.73	2	96.70%	N28	0.9459	2	96.70%
N29	4,512.24	3	93.50%	N9	0.9406	3	93.50%
N26	3,137.66	4	90.30%	N26	0.9354	4	90.30%
N6	3,085.16	5	87.00%	N20	0.9296	5	87.00%
N9	2,511.35	6	83.80%	N6	0.9218	6	83.80%
N31	2,324.08	7	80.60%	N17	0.9216	7	80.60%
N20	1,784.21	8	77.40%	N23	0.9216	8	77.40%
N11	1,685.89	9	74.10%	N5	0.921	9	74.10%
N17	1,329.32	10	70.90%	N25	0.911	10	70.90%
N28	1,278.17	11	67.70%	N10	0.9088	11	67.70%
N8	1,072.09	12	64.50%	N8	0.9075	12	64.50%
N10	1,015.58	13	61.20%	N18	0.9061	13	61.20%
N16	941.06	14	58.00%	N15	0.904	14	58.00%
N22	915.22	15	54.80%	N27	0.8891	15	54.80%
N15	889.70	16	51.60%	N12	0.8866	16	51.60%
N18	880.81	17	48.30%	N30	0.8852	17	48.30%
N30	856.89	18	45.10%	N16	0.8807	18	45.10%
N21	689.68	19	41.90%	N13	0.8799	19	41.90%
N13	679.78	20	38.70%	N7	0.8794	20	38.70%
N12	639.55	21	35.40%	N22	0.8742	21	35.40%
N7	517.44	22	32.20%	N14	0.8728	22	32.20%
N4	493.31	23	29.00%	N19	0.8703	23	29.00%
N1	484.69	24	25.80%	N21	0.8695	24	25.80%
N14	461.52	25	22.50%	N1	0.8686	25	22.50%
N25	447.94	26	19.30%	N31	0.8682	26	19.30%
N27	399.56	27	16.10%	N29	0.8596	27	16.10%
N3	369.81	28	12.90%	N4	0.8577	28	12.90%
N19	339.41	29	9.60%	N3	0.848	29	9.60%
N2	313.80	30	6.40%	N2	0.8372	30	6.40%
N24	209.73	31	3.20%	N24	0.8243	31	3.20%
N32	108.32	32	0.00%	N32	0.7648	32	0.00%

Results of Feature Ranking for ILDF based on Bounded and Unbounded Mahalanobis Distance for e-tongue (YB honey)

D^2				D_A^2			
Feature	**Criterion Value**	**Rank**	**Percent**	**Feature**	**Criterion Value**	**Rank**	**Percent**
T11	960.45	1	100.00%	T11	0.9134	1	100.00%
T2	218.66	2	88.80%	T1	0.8312	2	88.80%
T1	202.20	3	77.70%	T2	0.8204	3	77.70%
T10	164.84	4	66.60%	T9	0.7566	4	66.60%
T7	85.19	5	55.50%	T10	0.7477	5	55.50%
T3	57.36	6	44.40%	T8	0.7058	6	44.40%
T8	46.07	7	33.30%	T7	0.6164	7	33.30%
T9	37.04	8	22.20%	T3	0.6067	8	22.20%
T5	32.67	9	11.10%	T4	0.6042	9	11.10%
T4	22.20	10	0.00%	T5	0.5806	10	0.00%