Classification of Beans Using Principal Component Analysis: An Unsupervised Learning Classification Approach

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Abstract: Manual classification of beans is prone to errors and inefficiencies, necessitating an automated system for accurate and consistent results. This study focuses on the classification of beans, an essential task in agriculture and food processing, using Principal Component Analysis (PCA) to handle the complexity of beans' features. The research aimed to develop an efficient method for categorizing Nigerian beans varieties based on physical characteristics. PCA was employed to reduce the dimensionality of a dataset containing features like size, shape, and texture, followed by K-means clustering for categorization. Using the R programming language and libraries like *prcomp*, *ggplot2*, and *caret*, the analysis identified seven distinct clusters. The model achieved high precision for some beans types (such as BOMBAY and SIRA) but lower accuracy for others (such as DERMASON and SEKER). Overall, the study demonstrated the effectiveness of PCA in simplifying datasets and enhancing classification accuracy.

Keywords: Principal Component Analysis, classification, R-programming, K-means clustering, Dimensionality.

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1. Introduction

Beans, as a rich source of protein, fiber, and essential nutrients, play a crucial role in global food security and nutrition (Adegunwa *et al*., 2012). In Nigeria, they are a staple food and a key ingredient in traditional dishes, making their accurate classification vital for local consumption and international trade (Olalekan and Bosede, 2010). With advancements in computational techniques, beans classification has transitioned from traditional manual methods to automated, sophisticated approaches. Among these, Principal Component Analysis (PCA) has emerged as a powerful dimensionality reduction tool widely used in machine learning and data analysis (Jolliffe, 2002).

PCA is a statistical technique that transforms correlated variables into uncorrelated principal components, simplifying complex datasets (Abdi and Williams, 2010). In the context of beans classification, PCA effectively reduces datasets containing features such as size, shape, color, and texture, retaining only the most critical patterns for accurate classification (Çetin *et al*., 2018). The application of PCA offers multiple advantages: it reduces dataset dimensionality, facilitating visualization and analysis; filters out noise, enhancing classification accuracy; and improves computational efficiency, allowing algorithms to process data faster (Rodriguez *et al*., 2020). For Nigeria, where agriculture significantly contributes to the economy, adopting advanced techniques like PCA in bean classification can enhance quality control in production and export processes. This ensures Nigerian beans meet international standards, thereby increasing their global market value (Oluwafemi, 2020). Using PCA aligns with the broader adoption of data-driven approaches in Nigerian agriculture, as highlighted by Adeyemo *et al*. (2019).

Accurate bean classification impacts seed selection, crop improvement programs, and market segmentation. It also supports efforts to preserve the genetic diversity of local bean varieties and develop more resilient cultivars (Apeh *et al*., 2021). For international trade, precise classification ensures compliance with import regulations, helping Nigeria expand its agricultural exports (Onu and Okoye, 2021).

Beyond PCA, integrating it with technologies such as image processing can enable rapid and non-destructive beans classification systems. These systems could revolutionize post-harvest processing and large-scale sorting operations, improving efficiency in Nigeria's beans industry (Oladosu *et al*., 2022). Beans exhibit diverse physical and chemical properties, including size, shape, texture, color, protein content, and moisture levels (Kahraman and Özcan, 2008). The high dimensionality of these features poses challenges for traditional analysis methods, especially in Nigeria, where agro-ecological diversity leads to subtle cultivar differences (Apeh *et al*., 2021).

Manual classification, though accessible, is labor-intensive, time-consuming, and prone to error, particularly for large-scale operations. This inefficiency creates bottlenecks in the supply chain, reducing productivity and profitability (Onu and Okoye, 2021). Additionally, the growing demand for specialized beans varieties with specific characteristics necessitates sophisticated classification methods that can cater to diverse consumer and industrial requirements (Adeleke *et al*., 2023). A lack of standardized classification methods further complicates quality assurance and international trade, posing barriers to market expansion (Oladosu *et al*., 2022). While traditional methods like visual inspection and local knowledge (Apeh *et al*., 2021) or color parameter analysis (Venora *et al*., 2009) are accessible, they lack the precision and objectivity needed for global standards. As a result, more advanced techniques, such as Near-Infrared Spectroscopy (NIRS) and machine vision systems, have emerged. NIRS, for example, allows rapid, non-destructive analysis of beans based on chemical composition (Hacisalihoglu *et al*., 2010), while machine vision systems enable the extraction of complex morphological features (Granitto *et al*., 2002). The use of PCA in beans classification has been well-documented. Rodriguez *et al*. (2020) demonstrated its role in identifying significant features for improved classification accuracy, while Adeyemo *et al*. (2019) emphasized its potential in crop science. Additionally, studies like Kutsanedzie *et al*. (2018) show how PCA combined with NIRS can classify agricultural products like cocoa beans efficiently.

Given these insights, this study aims to employ PCA in bean classification to reduce the dimensionality of datasets containing various bean features, enabling accurate, efficient, and data-driven classification.

2. Theoretical Frame Work

This study employs a quantitative research approach aimed at classifying different varieties of beans using Principal Component Analysis (PCA). The research design also follows a structured process, involving data collection, feature extraction, PCA implementation, and the application of classification algorithms. By using PCA, the study reduces the dimensionality of the data, allowing for efficient and accurate classification of beans varieties based on their physical and chemical characteristics.

2.1 Data Description and Method

The dataset comprises seven varieties of beans cultivated in Nigeria: Barbunya, Bombay, Cali, Dermason, Horoz, Seeker, and Sira. It includes several key columns: Aspect Ratio, Eccentricity, Convex Area, Equiv Diameter, Extent, Solidity, Roundness, Compactness, ShapeFactor1, ShapeFactor2, ShapeFactor3, ShapeFactor4, and Class. These features capture various physical attributes of the beans, forming a multidimensional space for analysis and classification.

The 'Class' variable serves as the primary target for classification tasks. The dataset was constructed using high-resolution images of 13,611 grains from seven registered dry bean varieties. Physical characteristics such as size (length, width, thickness), shape, texture, and color were recorded. Advanced image processing tools and colorimeters were employed to ensure accurate feature extraction. The data underwent preprocessing steps to remove noise, standardize features, and prepare it for Principal Component Analysis (PCA).

2.1.1 Features Extraction

Feature extraction aims to quantify the relevant characteristics of each beans sample. This involves:

i. **Image Processing**: Extracting physical features such as size, shape, and texture from the images of beans.

ii. **Spectroscopy**: NIRS was used to gather chemical composition data, particularly protein content, moisture level, and fiber content.

The resulting dataset consist of multiple variables, each representing a feature of the beans samples.

2.1.2 Empirical Steps for Beans Classification by Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) reduces the dataset's dimensionality by transforming the original set of variables (beans characteristics) into a smaller set of uncorrelated variables while retaining most of the original variance. The empirical steps involved in the PCA procedure are outlined below

$$X_{Scaled} = \frac{X-\mu}{\sigma} \quad (1)$$

Where X is the original data ,μ is the mean , and σ is the standard deviation of 1

Matrix Calculation: The dataset's covariance matrix was calculated in order to capture the relationships between variables (such as size, shape, and protein content):

$$\mathbf{C} = \frac{1}{n-1} X^T X \quad (2)$$

Eigenvalue and Eigenvector Calculation: From the covariance matrix**,** eigenvalues and eigenvectors were computed. The eigenvalues measure the amount of variance explained by each principal component, while the eigenvectors provide the directions of the new feature space (principal components):

$$Cv_i = \lambda_i v_i \quad (3)$$

Where $\lambda_i$is the eigenvalue corresponding to the i_{th} eigen vector v_i.

Principal Component Calculation: The original data was transformed into a new set of variables, the principal components. The first principal component Z_1 captures the most variance, followed by the second, and so on:

$$Z_I = Xv_I \quad (4)$$

where X is the original data and v_I is the eigenvector for the i_{th} principal component. The transformed data, Z, is a lower-dimensional representation of the original data.

Variance Explained by Each Principal Component: The proportion of variance explained by each principal component was evaluated using its corresponding eigenvalue:

$$Variance\ Explained: (PC_i) = \frac{\lambda_i}{\sum_{j=1}^{p} \lambda_j} \quad (5)$$

Whereλ_i is the eigenvalue for the i_{th} component, and p is the total number of variables in the original dataset. A scree plot was used to determine the optimal number of principal components to retain.

Dimensionality Reduction: Only the most important principal components—typically the first five that account for the majority of the variance were kept for additional examination based on the variance explained. Classification was now based on these reduced components.

2.1.3 Classification Algorithms

After dimensionality reduction through PCA, the transformed data fed into classification algorithms to classify the beans samples. The following algorithms were used to evaluate the performance of the PCA-transformed data:

i. **k-Nearest Neighbors (k-NN)**: This algorithm classifies beans based on their distance from the nearest known samples in the principal component space.
ii. **Support Vector Machines (SVM)**: SVM was applied to classify beans by finding a hyperplane that best separates different bean varieties in the principal component space.
iii. **Artificial Neural Networks (ANN)**: ANN was used to explore more complex, non-linear relationships between the PCA-transformed features and bean classifications.

2.1.4 Performance Evaluation

The performance of the classification models applied to the PCA-reduced data were evaluated using the following metrics:

i. **Accuracy**: The overall percentage of correct classifications.
ii. **Precision, Recall, and F1-Score**: These metrics provide insights into the performance of the classifiers for individual beans varieties.
iii. **Confusion Matrix**: This was used to assess the frequency of misclassifications between different beans varieties.

2.2 Libraries Required for R-Programming

The analysis was performed using R-programming codes with the aids of the following libraries:

i. **prcomp**: For implementing PCA to reduce the dimensionality of the data.
ii. **ggplot2**: For data visualization, including scatter plots, scree plots, and PCA projections.
iii. **class**: For implementing the k-Nearest Neighbors (k-NN) classification model.
iv. **e1071**: For implementing the Support Vector Machine (SVM) classification model.
v. **randomForest**: For implementing the Random Forest classification model.
vi. **caret**: For performance evaluation, including generating confusion matrices and calculating accuracy, precision, and recall.

2.2.1 Steps involved for beans Classification

The classification of beans in this study involves the following stages:

Step I: First, an exploratory data analysis was conducted in or to understand the distribution and relationships among the variables.

Step II: apply PCA to reduce the dimensionality of the dataset while retaining the most significant information and then implement a classification algorithm, including k-Nearest using the PCA-transformed data.

Throughout the analysis, an R-programming language was used and its relevant libraries for data manipulation, visualization, and model implementation. The performance of this classification model was rigorously evaluated using metrics such as accuracy, precision, recall, and F1-score.

3. Data Analysis and Interpretations

3.1 Exploratory Data Analysis.

The dataset consists of 13,611 samples of seven (7) different beans type. There are a total of 16 features (variables). Figure 1 and 2 show the distributions of selected features which includes beans Area and Perimeter. From the graphs, it can be gathered that the area and perimeters of the dry bean samples are positively skewed.

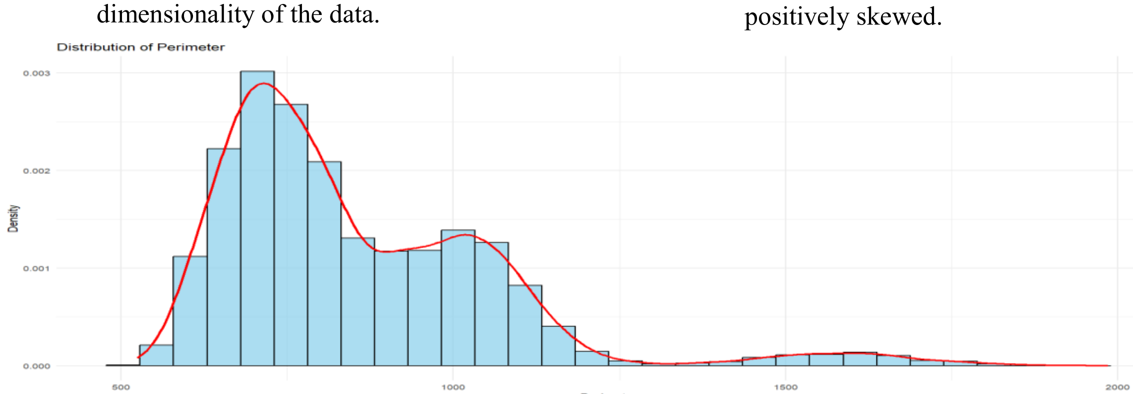

Figure 1: Distribution of Perimeter

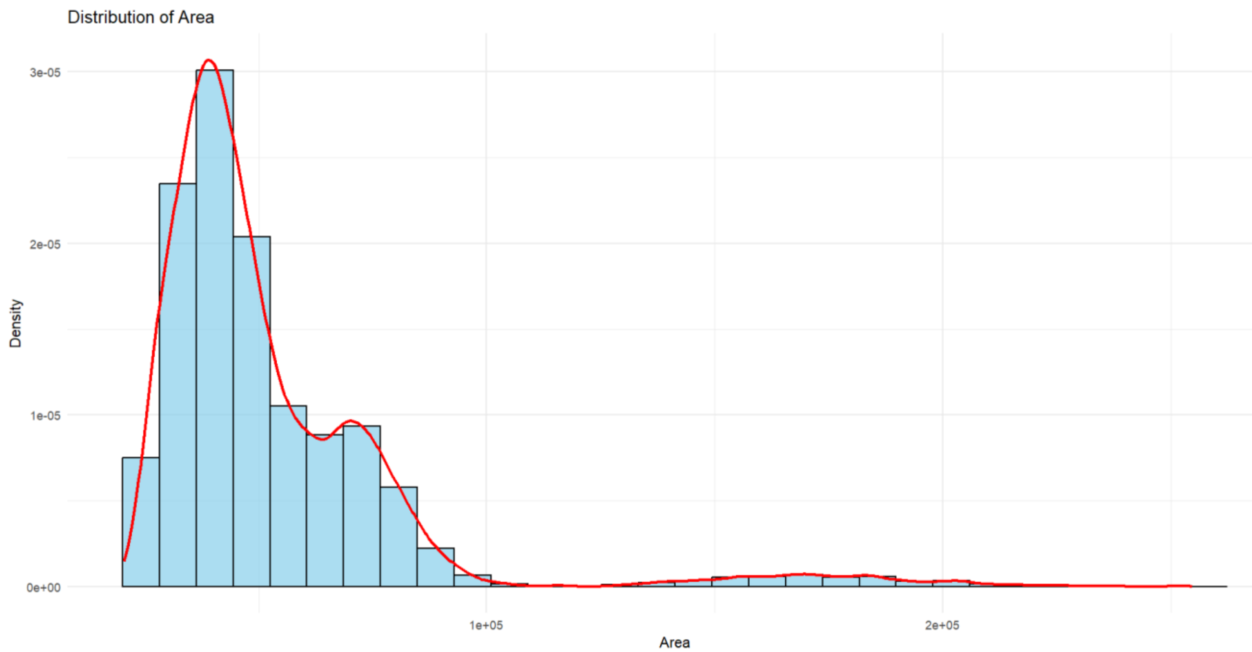

Figure 2: Distribution of Area

The correlation between the features when examined shows that there exist significant linear relationships between them. This violates the assumption of orthogonality among the variables. Hence, the justification of the use of Principal component analysis.

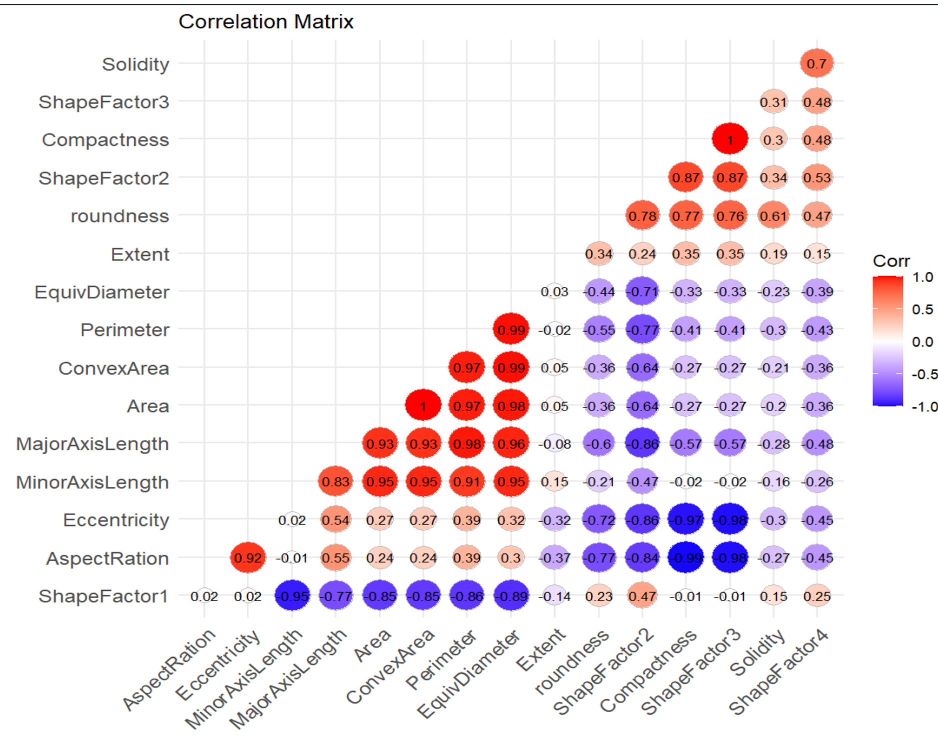

Figure 3: Correlation between features.

From Figure 3, it can be seen that there exists high positive (0.98) and negative (-0.99) correlation between some features. Apart from the high dimensionality of the dataset, another possible anomaly of the data is the problem of multicollinearity. Though multicollinearity is not a problem to be reckon with in unsupervised learning, however, researches affirmed that if multicollinearity exists in a dataset, it may lead to a misleading inference.

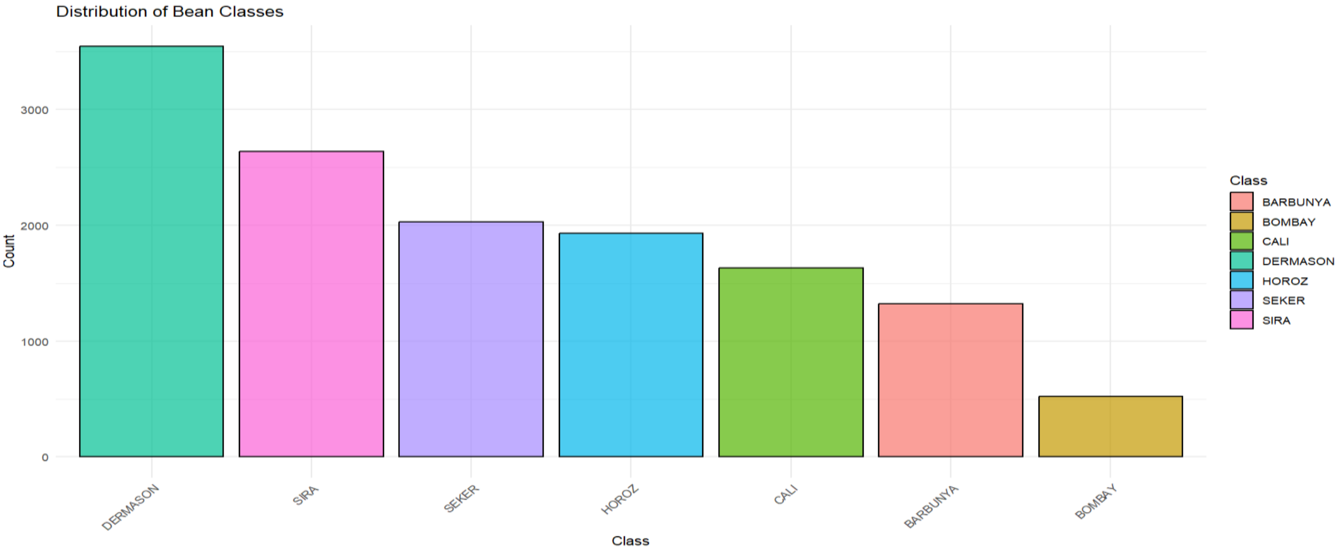

Figure 4: Distribution of Class of dry bean.

From Figure 4, it can be seen that there are 7 varieties of beans and that the most frequent beans type is DERMASON and the least frequent is BOMBAY. This shows that the dataset is not a balanced one.

3.2 Principal Component Analysis– Feature Contribution

The analysis of the first principal component (PC1) reveals crucial insights into the underlying structure of the dataset. It depicts that PC1 explains a total of 55% variation in the entire dataset. The visualization of feature loadings on PC1 illuminates the complex interplay between various physical characteristics of the beans and their importance in capturing data variance. Figure 5 represents a contrast between size-related features (positive loadings) and shape-related features (negative loadings).

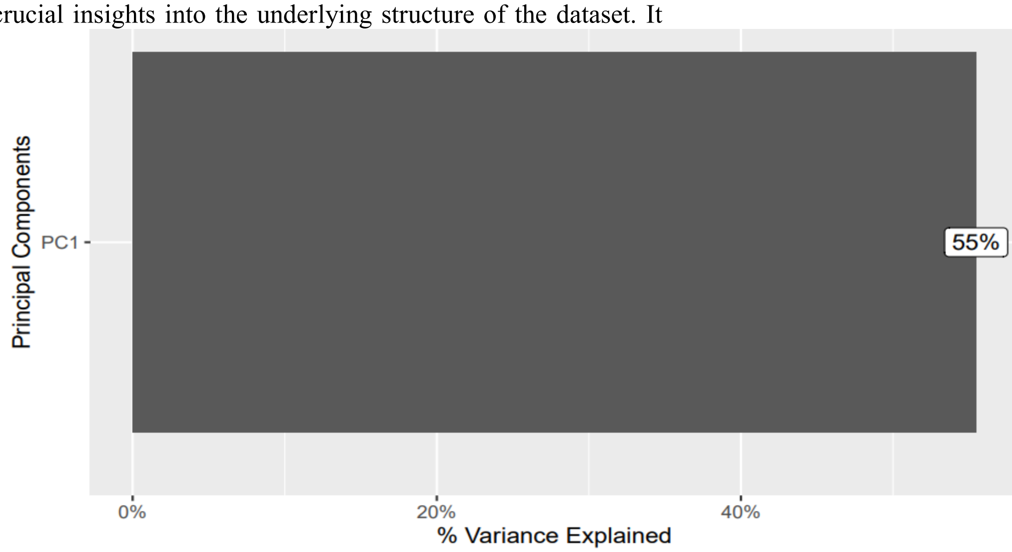

Figure 5: Percentage Variation explained by PC1

PC1 demonstrates a clear dichotomy in its representation of beans attributes. On one end of the spectrum, we observe strong positive contributions from features such as Major Axis Length, Perimeter, Convex Area, Equiv Diameter, and Area. These features collectively paint a picture of the bean's overall size and spatial extent. The substantial positive loadings of these variables suggest that PC1 heavily weighs the absolute dimensions of the beans, with larger beans scoring higher on this component.

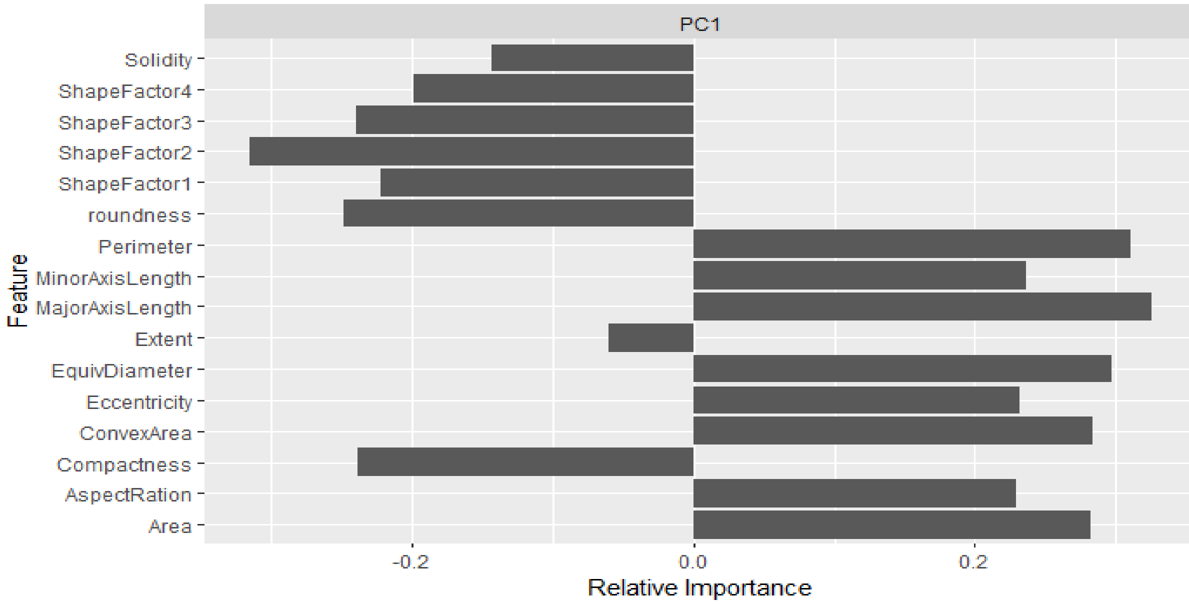

Figure 6: Bar chart of contrast between size-related features (positive loadings) and shape-related features (negative loadings).

Interpretation:
Conversely, PC1 also encapsulates information about the beans' shape complexity, albeit in an inverse relationship. Features like Compactness, ShapeFactor2, roundness, and ShapeFactor1 exhibit notable negative loadings. This negative association indicates that as beans become more deviate from simple, elongated forms, their scores on PC1 decrease. The inclusion of these shape-related features with negative loadings suggests that PC1 is not merely a measure of size, but rather a more nuanced representation that contrasts size with shape complexity. Interestingly, some features such as Solidity and Extent show minimal impact on PC1, as evidenced by their relatively small loadings, This doesn't necessarily diminish their importance in beans classification; rather, it suggests that these characteristics might be more prominent in subsequent principal components or may interact with other features in ways not captured by PC1 alone. The composition of PC1 offers valuable insights for our classification task. It suggests that the primary axis of variation in our dataset distinguishes between beans based on a combination of their size and shape characteristics. Larger beans with simpler shapes are likely to score higher on PC1, while smaller beans with more complex or compact shapes will tend to have lower scores. This interpretation of PC1 aligns well with the natural variation observed in beans morphology across different varieties. It captures the essence of how beans type often differ – some are characteristically large and elongated, while others are smaller with more intricate shapes. By encapsulating this fundamental contrast, PC1 provides a powerful tool for differentiating between beans classes.
Moreover, the clear structure revealed by PC1 suggests that our subsequent classification models may benefit significantly from this transformed feature space. The dimensional reduction achieved through PCA, with PC1 accounting for a substantial portion of data variance, promises to enhance the efficiency and potentially the accuracy of our classification algorithms.

3.3 Analysis of Principal Components
To delve deeper into Principal Component Analysis, loadings of the first two principal components (PC1 and PC2) for all features were examined.

Table 1: Loadings for PC1 and PC2

	PC1	PC2
Area	0.2925	0.236
Perimeter	0.3203	0.1683
MajorAxisLength	0.3343	0.0886
MinorAxisLength	0.2464	0.3365

AspectRation	0.2296	-0.3427
Eccentricity	0.232	-0.3312
ConvexArea	0.2931	0.2348
EquivDiameter	0.3073	0.2124
Extent	-0.058	0.2246
Solidity	-0.1329	0.0951
Roundness	-0.2494	0.2245
Compactness	-0.2383	0.3404
ShapeFactor1	-0.2309	-0.3263
ShapeFactor2	-0.3195	0.1429
ShapeFactor3	-0.239	0.3391

PC1 Analysis:
PC1 continues to show a strong contrast between size-related and shape-related features, as observed earlier. Features like Major Axis Length (0.3343), Perimeter (0.3203), and Equiv Diameter (0.3073) have the highest positive loadings, reinforcing our earlier interpretation that PC1 primarily captures the overall size of the beans. Conversely, shape-related features such as ShapeFactor2 (-0.3195), ShapeFactor3 (-0.2390), and Compactness (-0.2383) show substantial negative loadings, indicating that PC1 also inversely represents shape complexity.

PC2 Analysis:
PC2 reveals a different pattern of feature importance. Notably, Aspect Ratio (-0.3427) and Eccentricity (-0.3312) have the strongest negative loadings, while Compactness (0.3404) and ShapeFactor3 (0.3391) have the highest positive loadings. This suggests that PC2 primarily captures the elongation and regularity of the beans shape.
These two-dimensional representation allows for a more comprehensive classification approach. Beans can now be differentiated not only by their size but also by their shape characteristics. For instance, large, elongated beans would score high on PC1 but low on PC2, while small, compact beans would score low on PC1 and high on PC2.

3.4 K-Means Clustering On PCA Reduced Data

To further explore the effectiveness of PCA-reduced dataset in distinguishing between beans varieties, K-means clustering was applied to the first two principal components. The clusters are spread across different regions of the PC1 and PC2 space, indicating that each cluster represents beans with distinct combinations of size and shape characteristics.

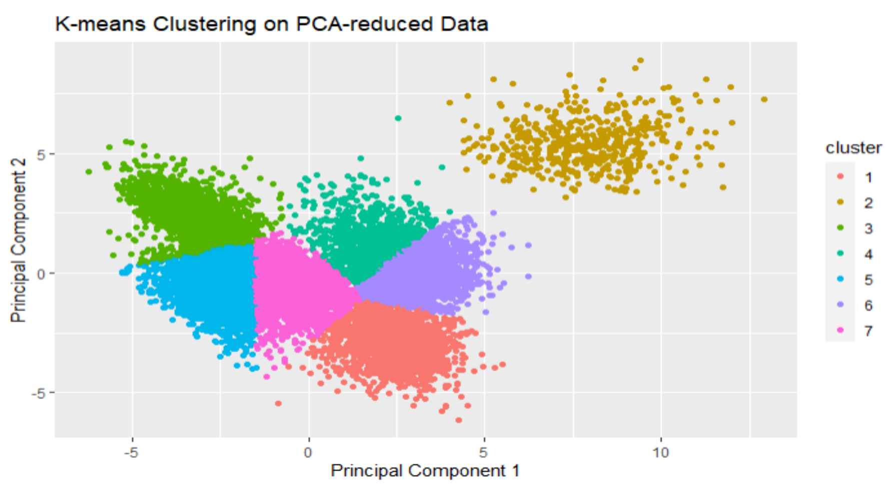

*Figure 7: **K-means clustering on PCA-reduced Data***

Figure 7, shows the scatter plot which reveals seven distinct clusters, each represented by a different color. This clear separation suggests that the first two principal components effectively capture the key differences between beans varieties.
Also, it can be noticed that the brown cluster represents larger, possibly more elongated beans, given its high values on both PC1 and PC2.The green cluster indicates beans that are smaller but still elongated or irregularly shaped and clusters near the

center (blue, pink, purple) represent beans with more average or balanced characteristics in terms of size and shape.
Hence, the success of K-means in identifying distinct clusters based solely on the first two principal components validates the PCA approach. Thus, it demonstrates that these two components, derived from original 15 features effectively capture the essential characteristics that differentiate beans varieties.

3.5 K-Means Clustering Visualization using Original Features

After applying K-means clustering to the PCA-reduced data, the results were visualized using two of the original features: Area and Perimeter. This approach helps to understand how the clusters identified in the PCA space relate to easily interpretable physical characteristics of the beans.

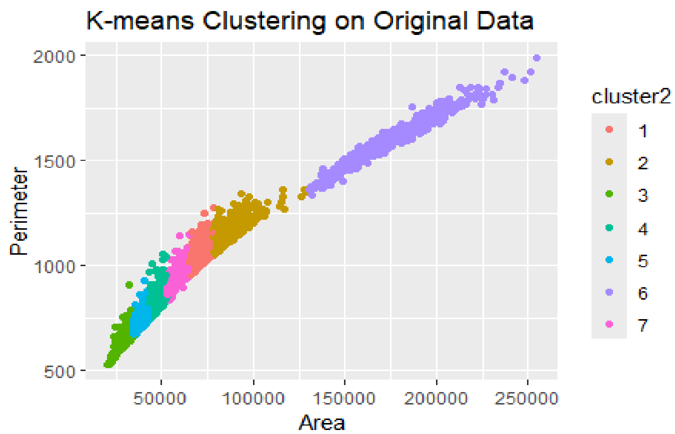

Figure 8: K-means Clustering of original data

From figure 8 which is the scatter plot it can be observed that there are clear separation between most clusters, indicating that the K-means algorithm has successfully identified distinct groups of beans based on their Area and Perimeter.

This scatter plot complements earlier PCA-based clustering by showing how the identified clusters manifest in terms of easily measurable physical characteristics. It demonstrates that the PCA-reduced representation effectively captures meaningful variations in bean size and shape, as evidenced by the clear cluster separations in the Area-Perimeter space.

The consistency between this clustering visualization and our earlier PCA-based analysis reinforces the validity of our approach. It suggests that the dimensionality reduction achieved through PCA has preserved the most important features for distinguishing between beans type, while potentially reducing noise and less informative variations.

4. Summary

The primary objective of the study was to develop a robust classification model for beans based on their physical characteristics, using dimensionality reduction techniques to simplify the complex dataset. By applying PCA, the study was able to reduce the original dataset into a smaller number of principal components that retained most of the data's variability.
The findings revealed that PCA was effective in identifying key attributes such as size, shape, and texture, which played significant roles in distinguishing between different types of beans. The k-means clustering algorithm, applied to the PCA-transformed data, grouped the beans into seven distinct clusters. The results suggest that while PCA and clustering can be effective for beans classification, further refinement of the model may be needed to improve classification accuracy for all types. The study has demonstrated the potential of using advanced statistical techniques such as PCA in agricultural applications, particularly for improving quality control and market categorization of beans in Nigeria.

5. Conclusion

In this study, Principal Component Analysis (PCA) was employed to classify different types of beans based on their physical characteristics. The application of PCA proved to be an effective dimensionality reduction technique, enabling the identification of key variables such as size, shape, and texture, which significantly contributed to the classification of beans. By reducing the complexity of the dataset, PCA facilitated the application of the k-means clustering algorithm, which grouped the beans into seven distinct clusters.
Consequently, PCA offers a powerful tool for simplifying complex datasets while retaining essential information, especially when there exist linear correlation among the features of the dataset, making it a valuable approach in beans classification. However, further research is needed to optimize the classification process and ensure its effectiveness across all beans types. This research contributes to the advancement of

statistical applications in agriculture, which can significantly impact food security and economic growth in Nigeria.

Source of data: https://www.muratkoklu.com/datasets

Conflict of interest: Authors hereby declare that there is no conflict of interest

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Appendix: Sample of data

ConvexArea	EquivDiameter	Extent	Solidity	roundness	Compactness	ShapeFactor1	ShapeFactor2	ShapeFactor3	ShapeFactor4	Class
28715	190.1411	0.763923	0.9889	0.958	0.91336	0.0073	0.0031	0.8342	0.99872	SEKER
29172	191.2728	0.783968	0.985	0.887	0.95386	0.007	0.0036	0.9099	0.99843	SEKER
29690	193.4109	0.778113	0.9896	0.9478	0.90877	0.0072	0.003	0.8259	0.99907	SEKER
30724	195.4671	0.782681	0.9767	0.9039	0.92833	0.007	0.0032	0.8618	0.9942	SEKER
30417	195.8965	0.773098	0.9909	0.9849	0.97052	0.0067	0.0037	0.9419	0.99917	SEKER
30600	196.3477	0.775688	0.9895	0.9439	0.92373	0.007	0.0032	0.8533	0.99924	SEKER
30970	196.9886	0.762402	0.9841	0.8531	0.93337	0.0069	0.0032	0.8712	0.99905	SEKER
30847	197.1243	0.770682	0.9894	0.9671	0.92548	0.007	0.0032	0.8565	0.99834	SEKER
31044	197.6597	0.771561	0.9884	0.9542	0.92566	0.007	0.0032	0.8568	0.99895	SEKER
31120	198.139	0.783683	0.9908	0.9703	0.91213	0.007	0.003	0.832	0.99906	SEKER
31280	198.4055	0.770805	0.9884	0.9463	0.92904	0.0069	0.0032	0.8631	0.99938	SEKER
31458	198.963	0.786377	0.9883	0.9582	0.94525	0.0068	0.0033	0.8935	0.99864	SEKER
31423	199.0142	0.761046	0.9899	0.9526	0.92716	0.0069	0.0031	0.8596	0.99756	SEKER
31492	199.1773	0.798759	0.9894	0.9481	0.92005	0.0069	0.0031	0.8465	0.99787	SEKER
31474	199.1773	0.781313	0.99	0.9526	0.93922	0.0068	0.0033	0.8821	0.99935	SEKER
31520	199.2412	0.76411	0.9891	0.9659	0.93551	0.0068	0.0032	0.8752	0.99909	SEKER
31573	199.3179	0.779193	0.9882	0.9441	0.92431	0.0069	0.0031	0.8543	0.99869	SEKER
31558	199.3211	0.762984	0.9888	0.9579	0.92678	0.0069	0.0031	0.8589	0.9992	SEKER
31593	199.5413	0.770322	0.9898	0.9634	0.93924	0.0068	0.0033	0.8822	0.99936	SEKER
31599	199.7422	0.774277	0.9916	0.9765	0.92136	0.0069	0.0031	0.8489	0.9993	SEKER
31604	199.8665	0.769197	0.9927	0.9735	0.90904	0.007	0.003	0.8264	0.99823	SEKER
31791	200.3628	0.768949	0.9918	0.9708	0.93721	0.0068	0.0032	0.8784	0.99849	SEKER
32197	200.4994	0.756965	0.9806	0.8731	0.92265	0.0069	0.0031	0.8513	0.99754	SEKER
32045	200.7025	0.761823	0.9873	0.9218	0.87369	0.0073	0.0026	0.7633	0.99909	SEKER
32009	200.823	0.740936	0.9896	0.9209	0.84824	0.0075	0.0024	0.7195	0.99495	SEKER
32026	200.8452	0.773184	0.9893	0.9519	0.9562	0.0066	0.0034	0.9143	0.99896	SEKER
32093	200.9117	0.777111	0.9878	0.9249	0.9314	0.0068	0.0032	0.8675	0.99924	SEKER
32020	201.0542	0.77559	0.9915	0.9685	0.91481	0.0069	0.003	0.8369	0.99898	SEKER
32173	201.1176	0.777674	0.9874	0.9421	0.9102	0.007	0.0029	0.8285	0.99872	SEKER
32052	201.2536	0.773877	0.9925	0.9696	0.89852	0.007	0.0028	0.8073	0.99952	SEKER
32168	201.2853	0.772354	0.9892	0.9474	0.94175	0.0067	0.0033	0.8869	0.99785	SEKER
32274	201.2916	0.774848	0.986	0.911	0.90317	0.007	0.0029	0.8157	0.99948	SEKER
32238	201.3359	0.785246	0.9876	0.9285	0.89517	0.0071	0.0028	0.8013	0.99884	SEKER
32184	201.5823	0.777656	0.9916	0.9769	0.93187	0.0068	0.0032	0.8684	0.99885	SEKER
32246	201.7623	0.772271	0.9915	0.981	0.94419	0.0067	0.0033	0.8915	0.99925	SEKER
32258	201.8254	0.774212	0.9918	0.9805	0.94804	0.0067	0.0033	0.8988	0.99922	SEKER
32391	201.8317	0.789741	0.9877	0.9385	0.95127	0.0066	0.0033	0.9049	0.99778	SEKER
32375	201.8979	0.761881	0.9889	0.9415	0.94819	0.0067	0.0033	0.8991	0.99806	SEKER
32349	201.9326	0.779449	0.99	0.9402	0.87425	0.0072	0.0026	0.7643	0.99778	SEKER
32308	201.9704	0.770515	0.9916	0.9675	0.89972	0.007	0.0028	0.8095	0.99876	SEKER
32395	201.9893	0.778069	0.9892	0.9454	0.9345	0.0067	0.0032	0.8733	0.99888	SEKER
32301	202.0303	0.779805	0.9924	0.9771	0.93568	0.0067	0.0032	0.8755	0.99859	SEKER
32481	202.0587	0.780879	0.9872	0.8995	0.8546	0.0074	0.0024	0.7303	0.99682	SEKER
ConvexArea	EquivDiameter	Extent	Solidity	roundness	Compactness	ShapeFactor1	ShapeFactor2	ShapeFactor3	ShapeFactor4	Class
50783	251.6943	0.734283	0.9798	0.8283	0.75791	0.0067	0.0014	0.5744	0.99359	BARBUNYA
50590	251.75	0.801911	0.9839	0.8432	0.83705	0.006	0.0018	0.7007	0.9958	BARBUNYA
50787	252.23	0.74012	0.9839	0.8131	0.80488	0.0063	0.0016	0.6478	0.9984	BARBUNYA
50699	252.2502	0.714797	0.9857	0.823	0.80335	0.0063	0.0016	0.6454	0.99365	BARBUNYA
51285	252.2905	0.737417	0.9748	0.7556	0.76624	0.0066	0.0014	0.5871	0.99739	BARBUNYA
50802	252.4015	0.806392	0.9849	0.8775	0.90325	0.0056	0.0023	0.8159	0.99693	BARBUNYA
51209	252.7317	0.762517	0.9796	0.789	0.80739	0.0062	0.0016	0.6519	0.99706	BARBUNYA
50937	252.7343	0.794599	0.9849	0.8256	0.81555	0.0062	0.0017	0.6651	0.99684	BARBUNYA
51525	253.5365	0.799943	0.9798	0.657	0.77889	0.0064	0.0015	0.6067	0.99473	BARBUNYA
51389	253.7599	0.712123	0.9842	0.8623	0.80731	0.0062	0.0016	0.6518	0.99707	BARBUNYA
51613	254.0307	0.769884	0.982	0.7768	0.80661	0.0062	0.0016	0.6506	0.99731	BARBUNYA
51454	254.1034	0.717538	0.9856	0.8282	0.80358	0.0062	0.0016	0.6457	0.99867	BARBUNYA
52164	254.3187	0.738622	0.9738	0.7865	0.82466	0.0061	0.0017	0.6801	0.99648	BARBUNYA
52063	254.694	0.719605	0.9786	0.818	0.81227	0.0062	0.0017	0.6598	0.9937	BARBUNYA
51805	254.7689	0.708914	0.984	0.8243	0.7885	0.0063	0.0015	0.6217	0.99893	BARBUNYA
51718	254.8614	0.777419	0.9864	0.8683	0.77735	0.0064	0.0014	0.6043	0.99803	BARBUNYA
51979	255.0911	0.715885	0.9832	0.8169	0.80379	0.0062	0.0016	0.6461	0.99414	BARBUNYA
52283	255.652	0.751688	0.9818	0.815	0.77278	0.0064	0.0014	0.5972	0.99468	BARBUNYA
52436	256.0998	0.74212	0.9824	0.8214	0.92569	0.0054	0.0024	0.8569	0.99771	BARBUNYA

52274	256.2589	0.783949	0.9866	0.874	0.82437	0.006	0.0017	0.6796	0.99918	BARBUNYA
52718	256.5022	0.797721	0.9802	0.7841	0.80437	0.0062	0.0016	0.647	0.99689	BARBUNYA
52208	256.5494	0.776451	0.9901	0.932	0.84294	0.0059	0.0018	0.7105	0.99751	BARBUNYA
52714	256.5543	0.773484	0.9807	0.8374	0.83751	0.0059	0.0018	0.7014	0.9945	BARBUNYA
52632	256.6511	0.746522	0.9829	0.8426	0.80219	0.0062	0.0016	0.6435	0.99792	BARBUNYA
52581	256.7701	0.713664	0.9848	0.8826	0.82476	0.006	0.0017	0.6802	0.99692	BARBUNYA
52774	257.0774	0.776327	0.9836	0.8116	0.78525	0.0063	0.0015	0.6166	0.99535	BARBUNYA
52906	257.1417	0.726403	0.9816	0.81	0.81955	0.006	0.0017	0.6717	0.99718	BARBUNYA
53108	257.5672	0.774113	0.9811	0.797	0.81273	0.0061	0.0016	0.6605	0.99871	BARBUNYA
53114	257.7649	0.678155	0.9825	0.8305	0.7741	0.0064	0.0014	0.5992	0.99671	BARBUNYA
53664	257.7723	0.709043	0.9725	0.6886	0.82833	0.006	0.0017	0.6861	0.98957	BARBUNYA
53407	258.1523	0.765723	0.98	0.8042	0.89085	0.0055	0.0022	0.7936	0.99807	BARBUNYA
53754	258.6549	0.748248	0.9775	0.7946	0.81875	0.006	0.0017	0.6703	0.99839	BARBUNYA
53574	258.7804	0.75292	0.9817	0.8383	0.8276	0.0059	0.0017	0.6849	0.99838	BARBUNYA
53696	258.9255	0.740952	0.9806	0.7886	0.83257	0.0059	0.0018	0.6932	0.99558	BARBUNYA
54100	259.3014	0.702683	0.9761	0.7695	0.77966	0.0063	0.0014	0.6079	0.99721	BARBUNYA
53871	259.3702	0.715789	0.9808	0.7634	0.80635	0.0061	0.0016	0.6502	0.99848	BARBUNYA
53489	259.3775	0.693016	0.9878	0.8506	0.80277	0.0061	0.0016	0.6444	0.99513	BARBUNYA
53855	259.4168	0.706552	0.9814	0.8233	0.80552	0.0061	0.0016	0.6489	0.99339	BARBUNYA
53879	259.5125	0.717888	0.9817	0.7879	0.78255	0.0063	0.0015	0.6124	0.99791	BARBUNYA
54102	260.267	0.751865	0.9834	0.8297	0.86211	0.0057	0.0019	0.7432	0.99834	BARBUNYA
54195	260.3819	0.696685	0.9825	0.7907	0.80022	0.0061	0.0015	0.6404	0.99735	BARBUNYA
54318	260.6605	0.717245	0.9824	0.8194	0.79691	0.0061	0.0015	0.6351	0.99844	BARBUNYA
54228	260.6629	0.766526	0.9841	0.7929	0.82931	0.0059	0.0017	0.6878	0.99647	BARBUNYA
54618	260.6727	0.706384	0.9771	0.7401	0.81202	0.006	0.0016	0.6594	0.99693	BARBUNYA
54727	261.0534	0.78909	0.978	0.7955	0.80432	0.0061	0.0016	0.6469	0.99741	BARBUNYA
54660	261.0558	0.782873	0.9792	0.7312	0.81582	0.006	0.0016	0.6656	0.99798	BARBUNYA
54684	261.1217	0.689215	0.9793	0.7656	0.776	0.0063	0.0014	0.6022	0.99522	BARBUNYA
54945	261.6161	0.719111	0.9783	0.7817	0.80424	0.0061	0.0016	0.6468	0.99745	BARBUNYA
54878	261.9055	0.736587	0.9817	0.8106	0.80276	0.0061	0.0016	0.6444	0.99809	BARBUNYA
54651	262.4858	0.717755	0.9902	0.8926	0.80117	0.0061	0.0015	0.6419	0.99768	BARBUNYA
55164	262.6652	0.769134	0.9823	0.7853	0.74244	0.0065	0.0012	0.5512	0.9972	BARBUNYA
55277	262.7694	0.788674	0.9811	0.77	0.77747	0.0062	0.0014	0.6045	0.99701	BARBUNYA
55744	263.0794	0.714044	0.9751	0.8012	0.80596	0.006	0.0016	0.6496	0.98958	BARBUNYA
55211	263.239	0.748405	0.9857	0.8457	0.8104	0.006	0.0016	0.6567	0.99834	BARBUNYA
55695	263.2777	0.728489	0.9775	0.6479	0.78793	0.0061	0.0015	0.6208	0.98849	BARBUNYA
55225	263.4759	0.690493	0.9873	0.8508	0.77487	0.0062	0.0014	0.6004	0.99859	BARBUNYA
55730	263.5267	0.671158	0.9787	0.7224	0.78453	0.0062	0.0014	0.6155	0.99639	BARBUNYA
55585	263.6981	0.769753	0.9825	0.8012	0.77569	0.0062	0.0014	0.6017	0.996	BARBUNYA
55557	263.7392	0.756243	0.9833	0.8594	0.86782	0.0056	0.0019	0.7531	0.99792	BARBUNYA
55858	263.8502	0.753013	0.9789	0.8279	0.85429	0.0056	0.0019	0.7298	0.99561	BARBUNYA
55278	263.8864	0.678224	0.9894	0.8839	0.7979	0.006	0.0015	0.6366	0.99319	BARBUNYA
55970	264.7703	0.732859	0.9837	0.7752	0.76895	0.0063	0.0013	0.5913	0.9934	BARBUNYA
56772	264.8688	0.787458	0.9705	0.7699	0.881	0.0055	0.002	0.7762	0.99137	BARBUNYA
55918	265.4139	0.793014	0.9894	0.8861	0.8158	0.0059	0.0016	0.6655	0.99665	BARBUNYA
56515	265.5338	0.714026	0.9799	0.8198	0.82218	0.0058	0.0016	0.676	0.99416	BARBUNYA
55945	265.5578	0.80264	0.99	0.8909	0.8085	0.0059	0.0016	0.6537	0.99754	BARBUNYA
56253	265.6584	0.728763	0.9854	0.8379	0.81037	0.0059	0.0016	0.6567	0.99709	BARBUNYA
56460	265.6704	0.718876	0.9818	0.8134	0.80362	0.006	0.0015	0.6458	0.99872	BARBUNYA
56806	266.0583	0.770262	0.9787	0.7778	0.84527	0.0057	0.0018	0.7145	0.9967	BARBUNYA
56424	266.0846	0.756506	0.9855	0.8656	0.85442	0.0056	0.0018	0.73	0.99401	BARBUNYA
56806	266.1133	0.744565	0.9791	0.8039	0.85314	0.0056	0.0018	0.7278	0.99437	BARBUNYA
56777	266.1707	0.799135	0.98	0.7763	0.76551	0.0062	0.0013	0.586	0.99113	BARBUNYA
56773	266.2114	0.70545	0.9804	0.7968	0.81682	0.0059	0.0016	0.6672	0.99761	BARBUNYA

ConvexArea	EquivDiameter	Extent	Solidity	roundness	Compactness	ShapeFactor1	ShapeFactor2	ShapeFactor3	ShapeFactor4	Class
115298	380.9913	0.748987	0.9888	0.8753	0.84409	0.004	0.0012	0.7125	0.99334	BOMBAY
118019	386.0211	0.746319	0.9917	0.9177	0.90632	0.0036	0.0015	0.8214	0.99613	BOMBAY
128220	401.3336	0.771313	0.9866	0.9028	0.84354	0.0038	0.0012	0.7116	0.99752	BOMBAY
129274	403.8872	0.782247	0.9911	0.8703	0.80132	0.0039	0.001	0.6421	0.99375	BOMBAY
130688	405.9171	0.799334	0.9902	0.8938	0.83804	0.0037	0.0011	0.7023	0.99708	BOMBAY
131148	406.5408	0.806315	0.9898	0.8867	0.82422	0.0038	0.0011	0.6793	0.99588	BOMBAY
131860	406.9524	0.751537	0.9864	0.8808	0.83614	0.0037	0.0011	0.6991	0.9917	BOMBAY
132831	408.7926	0.814988	0.9881	0.8725	0.78441	0.004	0.0009	0.6153	0.99033	BOMBAY
132905	409.1647	0.793368	0.9893	0.8826	0.84209	0.0037	0.0011	0.7091	0.99691	BOMBAY
133553	410.3548	0.727118	0.9903	0.9009	0.82439	0.0038	0.0011	0.6796	0.99604	BOMBAY
133434	410.5796	0.789965	0.9922	0.9323	0.84332	0.0037	0.0011	0.7112	0.99905	BOMBAY

134466	411.2799	0.686341	0.988	0.8902	0.80332	0.0039	0.001	0.6453	0.99095	BOMBAY
134325	411.3387	0.789361	0.9893	0.8852	0.82326	0.0038	0.0011	0.6778	0.99627	BOMBAY
135151	412.6845	0.744567	0.9897	0.8959	0.85751	0.0036	0.0012	0.7353	0.9979	BOMBAY
135500	413.0731	0.760706	0.989	0.8769	0.7978	0.0039	0.001	0.6365	0.99287	BOMBAY
135409	413.4413	0.789684	0.9914	0.8712	0.78957	0.0039	0.0009	0.6234	0.99623	BOMBAY
136192	414.9337	0.772423	0.9929	0.9031	0.83808	0.0037	0.0011	0.7024	0.99702	BOMBAY
137618	415.2113	0.78785	0.9839	0.891	0.79352	0.0039	0.0009	0.6297	0.99181	BOMBAY
137538	415.9696	0.754788	0.9881	0.8894	0.81652	0.0037	0.001	0.6667	0.9946	BOMBAY
139517	417.7671	0.676997	0.9825	0.8392	0.79288	0.0038	0.0009	0.6287	0.99139	BOMBAY
138970	417.828	0.789974	0.9867	0.8461	0.80475	0.0038	0.001	0.6476	0.99637	BOMBAY
138093	418.1981	0.798073	0.9947	0.9269	0.82325	0.0037	0.001	0.6777	0.99727	BOMBAY
139153	418.4416	0.778239	0.9883	0.8595	0.80504	0.0038	0.001	0.6481	0.99097	BOMBAY
138869	418.7914	0.809463	0.9919	0.8964	0.83864	0.0036	0.0011	0.7033	0.99409	BOMBAY
139207	419.0072	0.782239	0.9905	0.8712	0.80241	0.0038	0.001	0.6439	0.99365	BOMBAY
143275	419.2639	0.76737	0.9636	0.8142	0.77544	0.0039	0.0009	0.6013	0.97291	BOMBAY
139491	419.3474	0.79395	0.9901	0.9264	0.86693	0.0035	0.0012	0.7516	0.99732	BOMBAY
139249	419.5447	0.797365	0.9928	0.8918	0.82154	0.0037	0.001	0.6749	0.99431	BOMBAY
139739	419.5765	0.754837	0.9895	0.8914	0.8182	0.0037	0.001	0.6694	0.99454	BOMBAY
139826	420.1739	0.710733	0.9917	0.8697	0.82415	0.0037	0.001	0.6792	0.99626	BOMBAY
140144	420.3527	0.8237	0.9902	0.8859	0.83633	0.0036	0.0011	0.6995	0.99362	BOMBAY
140912	420.6539	0.738394	0.9863	0.8855	0.82577	0.0037	0.0011	0.6819	0.98781	BOMBAY
140892	421.481	0.73222	0.9903	0.8808	0.84007	0.0036	0.0011	0.7057	0.99748	BOMBAY
140541	421.6561	0.783916	0.9936	0.9225	0.88998	0.0034	0.0013	0.7921	0.99659	BOMBAY
141092	421.7271	0.765403	0.99	0.8927	0.82906	0.0036	0.0011	0.6873	0.99627	BOMBAY
141672	421.961	0.780276	0.9871	0.8591	0.80404	0.0038	0.001	0.6465	0.99394	BOMBAY
141966	422.6725	0.72124	0.9884	0.8598	0.81688	0.0037	0.001	0.6673	0.99429	BOMBAY
142672	423.5061	0.813762	0.9873	0.8849	0.84649	0.0036	0.0011	0.7165	0.99533	BOMBAY
142173	423.6519	0.815198	0.9915	0.8716	0.78711	0.0038	0.0009	0.6195	0.99567	BOMBAY
143530	424.2841	0.719165	0.9851	0.8695	0.80678	0.0037	0.001	0.6509	0.99404	BOMBAY
143783	424.4851	0.780601	0.9843	0.8542	0.81148	0.0037	0.001	0.6585	0.99241	BOMBAY
143680	424.9812	0.804617	0.9873	0.8682	0.80961	0.0037	0.001	0.6555	0.9918	BOMBAY
143704	425.1355	0.714711	0.9878	0.9075	0.81097	0.0037	0.001	0.6577	0.99531	BOMBAY
143074	425.4364	0.795125	0.9936	0.9406	0.84794	0.0035	0.0011	0.719	0.99744	BOMBAY
143764	425.562	0.767464	0.9894	0.8798	0.82403	0.0036	0.001	0.679	0.99789	BOMBAY
143783	425.8028	0.796192	0.9904	0.8747	0.81169	0.0037	0.001	0.6588	0.99527	BOMBAY
144325	426.0913	0.804164	0.988	0.9029	0.81976	0.0036	0.001	0.672	0.99431	BOMBAY
145400	427.5991	0.773694	0.9876	0.9139	0.82865	0.0036	0.001	0.6867	0.99449	BOMBAY
145734	428.276	0.748801	0.9885	0.8455	0.7977	0.0037	0.0009	0.6363	0.99324	BOMBAY
146415	428.3072	0.693121	0.984	0.847	0.80117	0.0037	0.0009	0.6419	0.99081	BOMBAY
145241	428.3132	0.797034	0.992	0.9019	0.84274	0.0035	0.0011	0.7102	0.99485	BOMBAY
145991	428.79	0.763525	0.9891	0.8691	0.81489	0.0036	0.001	0.664	0.9959	BOMBAY
146010	428.8702	0.761837	0.9894	0.8745	0.81693	0.0036	0.001	0.6674	0.99549	BOMBAY
145929	429.2352	0.759709	0.9916	0.8733	0.78743	0.0038	0.0009	0.62	0.99715	BOMBAY
146814	429.9154	0.704613	0.9888	0.8685	0.80229	0.0037	0.0009	0.6437	0.99576	BOMBAY
146709	430.096	0.786047	0.9903	0.8792	0.8193	0.0036	0.001	0.6712	0.99802	BOMBAY
147256	430.176	0.695958	0.987	0.8501	0.79184	0.0037	0.0009	0.627	0.99464	BOMBAY
147342	430.9847	0.757656	0.9901	0.8859	0.79897	0.0037	0.0009	0.6384	0.99615	BOMBAY
147648	431.1634	0.770384	0.9889	0.8537	0.81342	0.0036	0.001	0.6617	0.99261	BOMBAY
147529	431.1752	0.8069	0.9897	0.8671	0.79824	0.0037	0.0009	0.6372	0.99474	BOMBAY
149267	431.3789	0.731936	0.9791	0.8426	0.81981	0.0036	0.001	0.6721	0.99192	BOMBAY
148196	431.3804	0.735714	0.9862	0.8615	0.79835	0.0037	0.0009	0.6374	0.99316	BOMBAY
149274	431.6371	0.764794	0.9803	0.8436	0.79596	0.0037	0.0009	0.6336	0.99283	BOMBAY
150261	431.9217	0.755107	0.9751	0.8426	0.81765	0.0036	0.001	0.6686	0.98697	BOMBAY
148342	432.0646	0.815632	0.9884	0.8642	0.78409	0.0038	0.0009	0.6148	0.99529	BOMBAY
148492	432.424	0.819414	0.989	0.9115	0.80908	0.0036	0.001	0.6546	0.9918	BOMBAY
148762	432.5918	0.798366	0.988	0.8624	0.80059	0.0037	0.0009	0.6409	0.99621	BOMBAY
148198	432.6712	0.824321	0.9921	0.8857	0.81197	0.0036	0.001	0.6593	0.99718	BOMBAY
148317	432.6918	0.808845	0.9914	0.893	0.82052	0.0036	0.001	0.6732	0.99571	BOMBAY
148914	432.9478	0.744733	0.9886	0.8689	0.81498	0.0036	0.001	0.6642	0.99813	BOMBAY
149204	433.0507	0.774214	0.9872	0.8576	0.7721	0.0038	0.0008	0.5961	0.99249	BOMBAY
148921	433.8423	0.783804	0.9927	0.8809	0.80137	0.0037	0.0009	0.6422	0.99405	BOMBAY
149429	433.9935	0.760034	0.99	0.8967	0.83563	0.0035	0.0011	0.6983	0.99415	BOMBAY
149846	434.5725	0.778887	0.9898	0.8805	0.79051	0.0037	0.0009	0.6249	0.9959	BOMBAY
153846	435.3073	0.749169	0.9674	0.8269	0.8169	0.0036	0.001	0.6673	0.97549	BOMBAY
ConvexArea	**EquivDiameter**	**Extent**	**Solidity**	**roundness**	**Compactness**	**ShapeFactor1**	**ShapeFactor2**	**ShapeFactor3**	**ShapeFactor4**	**Class**
45972	240.7021	0.737779	0.9898	0.9084	0.81464	0.0065	0.0018	0.6636	0.99885	CALI

46074	241.1302	0.748378	0.9911	0.92	0.87727	0.006	0.0022	0.7696	0.99836	CALI
49026	248.1742	0.806539	0.9867	0.8928	0.79145	0.0065	0.0016	0.6264	0.99251	CALI
49720	250.401	0.777225	0.9904	0.9144	0.83081	0.0061	0.0018	0.6903	0.99851	CALI
51042	252.0153	0.726021	0.9773	0.7887	0.70555	0.0072	0.0011	0.4978	0.98874	CALI
51704	254.7089	0.733806	0.9855	0.8543	0.77148	0.0065	0.0014	0.5952	0.99013	CALI
52139	256.4253	0.786067	0.9905	0.8867	0.83256	0.006	0.0018	0.6932	0.99937	CALI
53082	258.4161	0.78919	0.9881	0.8463	0.76691	0.0064	0.0014	0.5881	0.99586	CALI
54085	261.2606	0.795386	0.9912	0.8439	0.73651	0.0066	0.0012	0.5425	0.99518	CALI
55293	262.3961	0.77005	0.978	0.8503	0.76558	0.0063	0.0013	0.5861	0.98832	CALI
54769	262.544	0.763245	0.9885	0.8299	0.73667	0.0066	0.0012	0.5427	0.98962	CALI
54907	263.0431	0.740449	0.9897	0.9072	0.86571	0.0056	0.0019	0.7494	0.99869	CALI
55370	263.8574	0.756607	0.9875	0.8487	0.74625	0.0065	0.0012	0.5569	0.99289	CALI
56394	265.8309	0.784799	0.9842	0.8645	0.76936	0.0062	0.0013	0.5919	0.98787	CALI
56205	265.9339	0.769137	0.9882	0.8172	0.74346	0.0064	0.0012	0.5527	0.99741	CALI
56517	265.9458	0.806437	0.9829	0.8345	0.76315	0.0063	0.0013	0.5824	0.98911	CALI
56288	266.087	0.759496	0.9879	0.8279	0.76363	0.0063	0.0013	0.5831	0.98922	CALI
56736	266.3596	0.779274	0.9821	0.8691	0.83516	0.0057	0.0017	0.6975	0.98864	CALI
56664	266.8754	0.73156	0.9872	0.849	0.76848	0.0062	0.0013	0.5906	0.99785	CALI
56563	266.9565	0.800881	0.9896	0.8734	0.77945	0.0061	0.0014	0.6075	0.99657	CALI
57445	267.6662	0.766621	0.9795	0.8346	0.71549	0.0066	0.0011	0.5119	0.98671	CALI
57032	267.9182	0.68265	0.9885	0.8344	0.76397	0.0062	0.0013	0.5836	0.99651	CALI
57280	268.5139	0.792185	0.9886	0.8355	0.75386	0.0063	0.0013	0.5683	0.99693	CALI
57180	268.6277	0.753978	0.9912	0.8823	0.77876	0.0061	0.0014	0.6065	0.9951	CALI
57531	268.6372	0.810302	0.9852	0.858	0.75471	0.0063	0.0013	0.5696	0.98952	CALI
57509	269.0043	0.806453	0.9883	0.8623	0.78755	0.006	0.0014	0.6202	0.99747	CALI
58127	269.437	0.791573	0.9809	0.8776	0.77023	0.0061	0.0013	0.5933	0.98448	CALI
57649	269.437	0.668649	0.989	0.8782	0.75826	0.0062	0.0013	0.575	0.99439	CALI
58763	270.3192	0.749328	0.9767	0.8493	0.74557	0.0063	0.0012	0.5559	0.98939	CALI
58471	270.6911	0.788559	0.9842	0.8362	0.74583	0.0063	0.0012	0.5563	0.98698	CALI
58093	270.851	0.819005	0.9918	0.8905	0.78642	0.006	0.0014	0.6185	0.99635	CALI
59196	271.2479	0.758944	0.9762	0.8645	0.81732	0.0057	0.0016	0.668	0.9856	CALI
58737	271.4051	0.807958	0.9849	0.8392	0.75675	0.0062	0.0013	0.5727	0.99105	CALI
59220	271.4262	0.726544	0.9771	0.8034	0.72878	0.0064	0.0011	0.5311	0.9793	CALI
58999	271.5317	0.808712	0.9815	0.8686	0.75287	0.0062	0.0012	0.5668	0.98903	CALI
58691	271.9698	0.784672	0.9898	0.8581	0.77682	0.006	0.0014	0.6035	0.99256	CALI
58986	271.9885	0.805295	0.985	0.8862	0.81238	0.0058	0.0015	0.66	0.98701	CALI
59974	272.3394	0.722658	0.9713	0.8104	0.74985	0.0062	0.0012	0.5623	0.98163	CALI
59677	273.2309	0.748838	0.9825	0.8511	0.77658	0.006	0.0013	0.6031	0.98718	CALI
59701	273.4778	0.753425	0.9839	0.8306	0.73782	0.0063	0.0012	0.5444	0.98909	CALI
60179	273.6686	0.782322	0.9775	0.832	0.74331	0.0063	0.0012	0.5525	0.98452	CALI
60278	273.7965	0.713816	0.9768	0.7946	0.72654	0.0064	0.0011	0.5279	0.98346	CALI
59576	273.9917	0.813816	0.9897	0.8448	0.7545	0.0062	0.0012	0.5693	0.99287	CALI
60458	274.1729	0.763616	0.9765	0.8572	0.78381	0.0059	0.0014	0.6144	0.99017	CALI
60026	274.1776	0.749689	0.9836	0.8551	0.76207	0.0061	0.0013	0.5808	0.98873	CALI
59939	274.5071	0.786339	0.9874	0.851	0.77637	0.006	0.0013	0.6028	0.99277	CALI
60037	274.5651	0.742737	0.9862	0.8099	0.73869	0.0063	0.0012	0.5457	0.99543	CALI
59999	274.8663	0.793077	0.989	0.8426	0.78046	0.0059	0.0014	0.6091	0.99416	CALI
60734	274.8802	0.714893	0.9771	0.8363	0.77339	0.006	0.0013	0.5981	0.99002	CALI
59877	274.9798	0.820036	0.9918	0.8613	0.7609	0.0061	0.0013	0.579	0.9932	CALI
60021	275.0029	0.673909	0.9896	0.8008	0.71591	0.0065	0.001	0.5125	0.99849	CALI
60023	275.04	0.713764	0.9898	0.8806	0.78975	0.0059	0.0014	0.6237	0.99451	CALI
60550	275.0631	0.785146	0.9814	0.8271	0.75993	0.0061	0.0013	0.5775	0.99113	CALI
60107	275.1672	0.74671	0.9894	0.8359	0.74354	0.0062	0.0012	0.5528	0.99546	CALI
60643	275.2783	0.760102	0.9814	0.8482	0.77877	0.0059	0.0013	0.6065	0.98955	CALI
60538	275.5141	0.780596	0.9848	0.8704	0.80974	0.0057	0.0015	0.6557	0.99331	CALI
61244	275.5926	0.765721	0.974	0.8058	0.72758	0.0063	0.0011	0.5294	0.98279	CALI
60714	275.8374	0.763837	0.9843	0.8264	0.78597	0.0059	0.0014	0.6177	0.98507	CALI
60962	275.8627	0.767637	0.9804	0.8606	0.79175	0.0058	0.0014	0.6269	0.98855	CALI
60533	275.8881	0.766685	0.9876	0.7864	0.70668	0.0065	0.001	0.4994	0.99307	CALI
60493	275.9066	0.705047	0.9883	0.8694	0.81534	0.0057	0.0015	0.6648	0.99542	CALI
61068	276.0289	0.692965	0.9799	0.8578	0.77832	0.0059	0.0013	0.6058	0.98712	CALI
60728	276.5404	0.694707	0.989	0.8506	0.77671	0.0059	0.0013	0.6033	0.99343	CALI
60547	276.644	0.809448	0.9927	0.8891	0.78703	0.0058	0.0014	0.6194	0.99623	CALI
62285	276.7843	0.705704	0.966	0.8127	0.74801	0.0061	0.0012	0.5595	0.97889	CALI
61767	277.3771	0.767893	0.9783	0.7987	0.71208	0.0064	0.001	0.5071	0.98453	CALI
61176	277.579	0.769607	0.9892	0.8765	0.80157	0.0057	0.0015	0.6425	0.99561	CALI

61008	277.7555	0.812171	0.9932	0.9015	0.78404	0.0058	0.0014	0.6147	0.99686	CALI
61556	277.8495	0.705773	0.985	0.8305	0.76077	0.006	0.0012	0.5788	0.99462	CALI
61353	278.2639	0.796328	0.9912	0.9026	0.79576	0.0058	0.0014	0.6332	0.99564	CALI
61512	278.5886	0.747138	0.991	0.8469	0.75616	0.006	0.0012	0.5718	0.99727	CALI
62063	278.7188	0.708959	0.9831	0.8618	0.81009	0.0056	0.0015	0.6562	0.98483	CALI
62070	278.7462	0.721796	0.9832	0.8085	0.74118	0.0062	0.0011	0.5494	0.99206	CALI
61842	278.9288	0.674604	0.9881	0.8292	0.76065	0.006	0.0012	0.5786	0.99303	CALI
61796	278.9836	0.750114	0.9892	0.825	0.75534	0.006	0.0012	0.5705	0.99896	CALI
61712	279.1547	0.76715	0.9918	0.8454	0.74226	0.0061	0.0012	0.5509	0.99325	CALI
62068	279.2619	0.792893	0.9868	0.7977	0.71825	0.0063	0.001	0.5159	0.99314	CALI
62711	279.4989	0.686113	0.9784	0.8213	0.75305	0.006	0.0012	0.5671	0.98871	CALI
62310	279.6514	0.712949	0.9857	0.8229	0.76831	0.0059	0.0013	0.5903	0.9932	CALI
62238	279.722	0.802332	0.9874	0.8307	0.75745	0.006	0.0012	0.5737	0.99379	CALI

ConvexArea	EquivDiameter	Extent	Solidity	roundness	Compactness	ShapeFactor1	ShapeFactor2	ShapeFactor3	ShapeFactor4	Class
33354	204.9989	0.635476	0.9896	0.8216	0.72433	0.0086	0.0015	0.5246	0.9924	HOROZ
34108	205.7954	0.672741	0.9752	0.8078	0.75844	0.0082	0.0017	0.5752	0.98435	HOROZ
33989	206.2404	0.809867	0.9829	0.8417	0.73256	0.0084	0.0015	0.5366	0.98914	HOROZ
34023	206.5828	0.808383	0.9852	0.8524	0.74425	0.0083	0.0016	0.5539	0.9964	HOROZ
34023	206.5828	0.808383	0.9852	0.8524	0.74425	0.0083	0.0016	0.5539	0.9964	HOROZ
33892	206.6998	0.774072	0.9901	0.8875	0.78109	0.0079	0.0018	0.6101	0.99842	HOROZ
34358	207.8394	0.75605	0.9875	0.8466	0.72701	0.0084	0.0015	0.5285	0.99135	HOROZ
34420	207.922	0.799482	0.9865	0.8305	0.74962	0.0082	0.0016	0.5619	0.99685	HOROZ
34420	207.922	0.799482	0.9865	0.8305	0.74962	0.0082	0.0016	0.5619	0.99685	HOROZ
34437	208.5671	0.772614	0.9921	0.8932	0.76637	0.008	0.0017	0.5873	0.99587	HOROZ
34639	208.6617	0.75156	0.9872	0.9022	0.78761	0.0077	0.0018	0.6203	0.99129	HOROZ
34936	208.7715	0.604603	0.9798	0.7764	0.703	0.0087	0.0013	0.4942	0.99054	HOROZ
34990	209.2132	0.703855	0.9825	0.7965	0.70189	0.0087	0.0013	0.4927	0.98624	HOROZ
34773	209.3257	0.634196	0.9897	0.8634	0.75707	0.008	0.0016	0.5732	0.98722	HOROZ
35278	209.8482	0.687608	0.9804	0.8214	0.7401	0.0082	0.0015	0.5478	0.99216	HOROZ
35404	210.9556	0.692174	0.9872	0.8763	0.77421	0.0078	0.0017	0.5994	0.99753	HOROZ
35769	211.5192	0.64141	0.9824	0.8196	0.72287	0.0083	0.0014	0.5225	0.98823	HOROZ
35860	211.868	0.684656	0.9831	0.8602	0.79016	0.0076	0.0018	0.6244	0.9896	HOROZ
36088	212.4951	0.822182	0.9827	0.8095	0.76399	0.0078	0.0016	0.5837	0.99002	HOROZ
35978	212.6389	0.722097	0.987	0.8135	0.72281	0.0083	0.0014	0.5225	0.99419	HOROZ
36384	213.3651	0.779316	0.9827	0.7843	0.69589	0.0086	0.0012	0.4843	0.99411	HOROZ
36549	213.4934	0.728609	0.9795	0.8146	0.72344	0.0082	0.0014	0.5234	0.98765	HOROZ
36265	213.705	0.707922	0.9891	0.9055	0.80699	0.0074	0.0019	0.6512	0.99774	HOROZ
36592	214.5197	0.76198	0.9877	0.8362	0.71533	0.0083	0.0013	0.5117	0.99518	HOROZ
36979	215.4525	0.679223	0.9859	0.8571	0.75944	0.0078	0.0016	0.5767	0.99213	HOROZ
37093	215.5765	0.745507	0.984	0.8309	0.72878	0.0081	0.0014	0.5311	0.99103	HOROZ
37023	215.8245	0.704976	0.9881	0.8584	0.73625	0.008	0.0015	0.5421	0.99663	HOROZ
36969	215.8982	0.636236	0.9903	0.8213	0.70716	0.0083	0.0013	0.5001	0.99632	HOROZ
37285	216.2194	0.788786	0.9848	0.8714	0.79739	0.0074	0.0018	0.6358	0.99761	HOROZ
37393	216.4577	0.711353	0.9841	0.8022	0.72004	0.0082	0.0014	0.5185	0.99125	HOROZ
37726	217.1624	0.760929	0.9818	0.8327	0.71955	0.0081	0.0013	0.5178	0.9954	HOROZ
37537	217.309	0.675033	0.9881	0.808	0.71395	0.0082	0.0013	0.5097	0.99235	HOROZ
37902	218.3056	0.661401	0.9875	0.8394	0.72998	0.008	0.0014	0.5329	0.99144	HOROZ
38113	218.3756	0.80167	0.9827	0.7883	0.73372	0.0079	0.0014	0.5383	0.98814	HOROZ
38008	218.4252	0.624017	0.9859	0.8074	0.69481	0.0084	0.0012	0.4828	0.99557	HOROZ
38070	218.5184	0.676949	0.9851	0.8021	0.70911	0.0082	0.0013	0.5028	0.99736	HOROZ
38280	218.8008	0.678211	0.9822	0.8416	0.73137	0.008	0.0014	0.5349	0.99325	HOROZ
38887	219.1962	0.796875	0.9704	0.7568	0.73707	0.0079	0.0014	0.5433	0.97473	HOROZ
38194	219.3123	0.748054	0.9891	0.8974	0.77476	0.0075	0.0017	0.6003	0.99666	HOROZ
38242	219.3268	0.729363	0.9879	0.8698	0.77436	0.0075	0.0017	0.5996	0.99784	HOROZ
38251	219.3501	0.780587	0.9879	0.8085	0.69953	0.0083	0.0012	0.4893	0.99417	HOROZ
38615	219.8805	0.602807	0.9833	0.7872	0.69332	0.0084	0.0012	0.4807	0.99051	HOROZ
38480	220.1352	0.70294	0.9891	0.837	0.72312	0.008	0.0013	0.5229	0.99902	HOROZ
39200	220.2797	0.643924	0.9722	0.6452	0.71017	0.0081	0.0013	0.5043	0.99332	HOROZ
38857	220.6926	0.808561	0.9845	0.8444	0.75499	0.0076	0.0015	0.57	0.99439	HOROZ
38844	220.8109	0.827191	0.9858	0.8094	0.72159	0.008	0.0013	0.5207	0.99344	HOROZ
38773	221.194	0.796976	0.9911	0.8442	0.7216	0.008	0.0013	0.5207	0.9939	HOROZ
38773	221.194	0.796976	0.9911	0.8442	0.7216	0.008	0.0013	0.5207	0.9939	HOROZ
38914	221.3177	0.801826	0.9886	0.8318	0.72661	0.0079	0.0014	0.528	0.99259	HOROZ
39015	221.496	0.675005	0.9876	0.8046	0.69936	0.0082	0.0012	0.4891	0.99736	HOROZ
39096	221.7976	0.605216	0.9883	0.8155	0.70392	0.0082	0.0012	0.4955	0.99606	HOROZ
39550	222.3594	0.790413	0.9819	0.826	0.74129	0.0077	0.0014	0.5495	0.98853	HOROZ

39651	222.5254	0.650025	0.9808	0.7804	0.69648	0.0082	0.0012	0.4851	0.98798	HOROZ
39651	222.5254	0.650025	0.9808	0.7804	0.69648	0.0082	0.0012	0.4851	0.98798	HOROZ
39358	222.7513	0.630277	0.9901	0.8242	0.70899	0.0081	0.0013	0.5027	0.99526	HOROZ
39590	223.288	0.694291	0.9891	0.8926	0.79368	0.0072	0.0018	0.6299	0.99249	HOROZ
40240	223.4134	0.662532	0.9742	0.7838	0.6942	0.0082	0.0012	0.4819	0.98141	HOROZ
39693	223.439	0.702517	0.9879	0.8285	0.70825	0.008	0.0012	0.5016	0.99642	HOROZ
39983	223.9115	0.74141	0.9848	0.8187	0.71674	0.0079	0.0013	0.5137	0.99135	HOROZ
40004	223.9968	0.732363	0.9851	0.8163	0.72271	0.0079	0.0013	0.5223	0.98618	HOROZ
39892	224.0934	0.693797	0.9887	0.8528	0.74989	0.0076	0.0015	0.5623	0.99342	HOROZ
39998	224.1871	0.604743	0.9869	0.8181	0.71193	0.008	0.0013	0.5068	0.99292	HOROZ
40420	224.3716	0.589431	0.9782	0.7798	0.7072	0.008	0.0012	0.5001	0.98327	HOROZ
40200	224.4227	0.812676	0.984	0.8482	0.73911	0.0077	0.0014	0.5463	0.99201	HOROZ
40203	224.5333	0.658463	0.9849	0.7983	0.70597	0.008	0.0012	0.4984	0.99163	HOROZ
40333	224.6098	0.695506	0.9824	0.8529	0.77608	0.0073	0.0016	0.6023	0.98996	HOROZ
40470	224.6835	0.683674	0.9797	0.7948	0.72887	0.0078	0.0014	0.5312	0.98919	HOROZ
40152	224.7062	0.789665	0.9877	0.7817	0.67836	0.0084	0.0011	0.4602	0.99697	HOROZ
40385	224.8534	0.612226	0.9833	0.7597	0.68011	0.0083	0.0011	0.4626	0.99563	HOROZ
40364	225.0034	0.634993	0.9851	0.8281	0.73817	0.0077	0.0014	0.5449	0.99298	HOROZ
40598	225.0176	0.613102	0.9795	0.7812	0.67316	0.0084	0.0011	0.4531	0.98842	HOROZ
40336	225.0204	0.797305	0.9859	0.8107	0.71576	0.0079	0.0013	0.5123	0.99179	HOROZ
40559	225.077	0.772883	0.981	0.8556	0.7598	0.0074	0.0015	0.5773	0.97954	HOROZ
40483	225.1534	0.628155	0.9835	0.8062	0.7042	0.008	0.0012	0.4959	0.98431	HOROZ
40310	225.159	0.628673	0.9878	0.8395	0.72127	0.0078	0.0013	0.5202	0.9963	HOROZ
40836	225.2382	0.808543	0.9757	0.7107	0.71061	0.008	0.0013	0.505	0.98826	HOROZ
40193	225.3625	0.729926	0.9924	0.8353	0.70727	0.008	0.0012	0.5002	0.9973	HOROZ
40451	225.4811	0.805255	0.9871	0.8127	0.70246	0.008	0.0012	0.4935	0.99255	HOROZ
40845	225.7379	0.669555	0.9799	0.758	0.74267	0.0076	0.0014	0.5516	0.98105	HOROZ
40557	225.8845	0.820768	0.9881	0.8213	0.69402	0.0081	0.0012	0.4817	0.99456	HOROZ
41384	225.8986	0.733403	0.9685	0.7704	0.73019	0.0077	0.0014	0.5332	0.97731	HOROZ
40565	225.9296	0.658292	0.9883	0.8406	0.72652	0.0078	0.0013	0.5278	0.99612	HOROZ
40619	225.9606	0.710633	0.9872	0.8224	0.724	0.0078	0.0013	0.5242	0.99709	HOROZ
40762	225.9859	0.624533	0.984	0.8101	0.69707	0.0081	0.0012	0.4859	0.99244	HOROZ
40880	226.5402	0.613314	0.986	0.8056	0.70442	0.008	0.0012	0.4962	0.98999	HOROZ
40810	226.588	0.716999	0.9881	0.7953	0.70106	0.008	0.0012	0.4915	0.9913	HOROZ
40826	226.6638	0.675998	0.9884	0.7951	0.70056	0.008	0.0012	0.4908	0.99617	HOROZ
40814	226.8519	0.651399	0.9903	0.8346	0.71758	0.0078	0.0013	0.5149	0.99372	HOROZ
41117	227.0399	0.598448	0.9846	0.7888	0.67897	0.0083	0.0011	0.461	0.98814	HOROZ
41041	227.0455	0.630462	0.9865	0.808	0.70825	0.0079	0.0012	0.5016	0.99088	HOROZ
40985	227.2361	0.692183	0.9895	0.8068	0.68348	0.0082	0.0011	0.4671	0.99362	HOROZ
41240	227.3257	0.623916	0.9842	0.7989	0.69833	0.008	0.0012	0.4877	0.99087	HOROZ
41539	227.5552	0.625436	0.9791	0.8056	0.70717	0.0079	0.0012	0.5001	0.989	HOROZ
41155	227.5552	0.619124	0.9882	0.7912	0.70105	0.008	0.0012	0.4915	0.99519	HOROZ
41333	227.6531	0.63607	0.9848	0.8229	0.7138	0.0078	0.0013	0.5095	0.99291	HOROZ
41251	227.6727	0.803089	0.9869	0.8375	0.71388	0.0078	0.0013	0.5096	0.99631	HOROZ
41473	227.8348	0.70442	0.983	0.7759	0.69107	0.0081	0.0011	0.4776	0.99473	HOROZ
41636	227.9326	0.78757	0.98	0.8199	0.70464	0.0079	0.0012	0.4965	0.9836	HOROZ
41636	227.9326	0.78757	0.98	0.8199	0.70464	0.0079	0.0012	0.4965	0.9836	HOROZ
41600	228.5991	0.619611	0.9866	0.8103	0.69014	0.0081	0.0011	0.4763	0.99508	HOROZ
41693	228.7189	0.612931	0.9854	0.7924	0.68678	0.0081	0.0011	0.4717	0.99244	HOROZ
41550	228.7634	0.667132	0.9892	0.8231	0.70123	0.0079	0.0012	0.4917	0.99612	HOROZ
41547	228.7968	0.791445	0.9896	0.8008	0.67381	0.0083	0.0011	0.454	0.99675	HOROZ
41692	228.819	0.729657	0.9863	0.8487	0.74079	0.0075	0.0014	0.5488	0.99249	HOROZ
41668	228.833	0.810097	0.987	0.8413	0.73696	0.0075	0.0014	0.5431	0.99625	HOROZ
41661	228.9108	0.7529	0.9879	0.8471	0.73536	0.0076	0.0014	0.5408	0.99486	HOROZ
42802	229.0638	0.783073	0.9628	0.8047	0.7554	0.0074	0.0015	0.5706	0.96704	HOROZ
41914	229.1388	0.637554	0.9838	0.81	0.70415	0.0079	0.0012	0.4958	0.99019	HOROZ
41825	229.1443	0.619874	0.986	0.7801	0.68154	0.0082	0.0011	0.4645	0.99347	HOROZ
41796	229.1471	0.614816	0.9867	0.8124	0.72586	0.0077	0.0013	0.5269	0.99299	HOROZ
41710	229.1582	0.813154	0.9888	0.8284	0.69802	0.008	0.0012	0.4872	0.99674	HOROZ
42065	229.1638	0.699085	0.9805	0.774	0.72718	0.0076	0.0013	0.5288	0.99407	HOROZ
41858	229.4803	0.66477	0.9881	0.8167	0.72015	0.0077	0.0013	0.5186	0.99626	HOROZ
42028	229.5468	0.633966	0.9847	0.7883	0.72627	0.0076	0.0013	0.5275	0.99474	HOROZ
41936	229.7824	0.664142	0.9889	0.829	0.72512	0.0076	0.0013	0.5258	0.99464	HOROZ
41862	229.8295	0.805366	0.991	0.919	0.82581	0.0067	0.0019	0.682	0.99705	HOROZ
42304	230.0012	0.658562	0.9821	0.7891	0.71508	0.0077	0.0012	0.5113	0.9916	HOROZ
42522	230.6259	0.652719	0.9824	0.8264	0.74649	0.0074	0.0014	0.5572	0.99564	HOROZ

42439	230.8521	0.631789	0.9863	0.7801	0.71164	0.0078	0.0012	0.5064	0.99634	HOROZ
42538	230.8549	0.704663	0.984	0.8233	0.72709	0.0076	0.0013	0.5287	0.99127	HOROZ
42521	230.9679	0.668624	0.9853	0.8277	0.73104	0.0075	0.0013	0.5344	0.99385	HOROZ
42593	231.1883	0.684885	0.9856	0.781	0.68567	0.008	0.0011	0.4701	0.99052	HOROZ
42593	231.1883	0.684885	0.9856	0.781	0.68567	0.008	0.0011	0.4701	0.99052	HOROZ
42648	231.1966	0.601956	0.9844	0.8012	0.70683	0.0078	0.0012	0.4996	0.9902	HOROZ
42857	231.1966	0.609197	0.9796	0.7397	0.69122	0.008	0.0011	0.4778	0.99204	HOROZ
42467	231.2324	0.691783	0.9889	0.8783	0.77522	0.0071	0.0016	0.601	0.99657	HOROZ
42673	231.2544	0.664042	0.9843	0.8553	0.76157	0.0072	0.0015	0.58	0.99387	HOROZ
42836	231.3728	0.668251	0.9815	0.7443	0.66573	0.0083	0.001	0.4432	0.98179	HOROZ
42898	231.447	0.677783	0.9807	0.8124	0.7041	0.0078	0.0012	0.4958	0.98315	HOROZ
42586	231.678	0.834046	0.9899	0.7971	0.69117	0.008	0.0011	0.4777	0.99497	HOROZ
42586	231.678	0.834046	0.9899	0.7971	0.69117	0.008	0.0011	0.4777	0.99497	HOROZ
42921	231.7604	0.817511	0.9829	0.7865	0.72952	0.0075	0.0013	0.5322	0.99352	HOROZ
42842	231.7796	0.746515	0.9849	0.8059	0.72671	0.0076	0.0013	0.5281	0.9961	HOROZ
42828	231.9636	0.710658	0.9867	0.7838	0.69564	0.0079	0.0011	0.4839	0.99457	HOROZ
43049	232.2735	0.807412	0.9843	0.7604	0.69748	0.0079	0.0011	0.4865	0.99547	HOROZ
43060	232.3173	0.781364	0.9844	0.8201	0.70833	0.0077	0.0012	0.5017	0.98418	HOROZ
43064	232.353	0.703219	0.9846	0.831	0.73	0.0075	0.0013	0.5329	0.98729	HOROZ
42820	232.4844	0.609388	0.9914	0.7779	0.66815	0.0082	0.001	0.4464	0.99275	HOROZ
42820	232.4844	0.609388	0.9914	0.7779	0.66815	0.0082	0.001	0.4464	0.99275	HOROZ
43079	232.635	0.681738	0.9867	0.8238	0.7191	0.0076	0.0013	0.5171	0.99697	HOROZ
43067	232.7636	0.645324	0.988	0.8487	0.74291	0.0074	0.0014	0.5519	0.99273	HOROZ
43188	232.9331	0.726309	0.9867	0.8267	0.7117	0.0077	0.0012	0.5065	0.99396	HOROZ
43163	233.0096	0.806133	0.9879	0.8239	0.71837	0.0076	0.0012	0.5161	0.99268	HOROZ
43350	233.0861	0.707136	0.9843	0.856	0.79313	0.0069	0.0017	0.6291	0.99639	HOROZ
43227	233.108	0.836414	0.9873	0.7923	0.68371	0.008	0.0011	0.4675	0.99076	HOROZ
43246	233.1489	0.810498	0.9872	0.8658	0.75313	0.0073	0.0014	0.5672	0.99044	HOROZ
43198	233.1899	0.8096	0.9887	0.7705	0.66556	0.0082	0.001	0.443	0.99614	HOROZ
43315	233.1953	0.806229	0.986	0.8047	0.69437	0.0079	0.0011	0.4821	0.98932	HOROZ
43391	233.3236	0.599846	0.9854	0.7748	0.68799	0.0079	0.0011	0.4733	0.99061	HOROZ
43284	233.37	0.717107	0.9882	0.8816	0.7977	0.0068	0.0017	0.6363	0.99526	HOROZ
43293	233.3863	0.800764	0.9882	0.8374	0.72347	0.0075	0.0013	0.5234	0.99677	HOROZ
43434	233.49	0.620443	0.9858	0.783	0.69703	0.0078	0.0011	0.4859	0.99619	HOROZ
43328	233.5963	0.727561	0.9891	0.8083	0.68908	0.0079	0.0011	0.4748	0.9972	HOROZ
44715	233.9857	0.66821	0.9616	0.576	0.67137	0.0081	0.001	0.4507	0.99224	HOROZ
43627	234.0265	0.709959	0.986	0.7932	0.68541	0.0079	0.0011	0.4698	0.99365	HOROZ
43500	234.0646	0.7405	0.9892	0.8189	0.7225	0.0075	0.0013	0.522	0.99288	HOROZ
43755	234.1951	0.772405	0.9845	0.7845	0.67097	0.0081	0.001	0.4502	0.98972	HOROZ
43710	234.2549	0.697666	0.986	0.8146	0.71368	0.0076	0.0012	0.5093	0.99154	HOROZ

ConvexArea	EquivDiameter	Extent	Solidity	roundness	Compactness	ShapeFactor1	ShapeFactor2	ShapeFactor3	ShapeFactor4	Class
32065	200.3278	0.758033	0.983	0.8651	0.78537	0.0081	0.0019	0.6168	0.99702	SIRA
32462	201.0637	0.694284	0.9781	0.8838	0.82368	0.0077	0.0022	0.6785	0.98274	SIRA
33185	204.5356	0.775569	0.9901	0.925	0.87481	0.0071	0.0026	0.7653	0.99682	SIRA
33564	205.5385	0.774835	0.9886	0.9275	0.85296	0.0073	0.0024	0.7275	0.99813	SIRA
33583	205.619	0.752663	0.9888	0.9013	0.79057	0.0078	0.0019	0.625	0.99665	SIRA
33692	205.9655	0.698696	0.9889	0.8823	0.79998	0.0077	0.002	0.64	0.99837	SIRA
33812	206.4101	0.827284	0.9896	0.8834	0.77753	0.0079	0.0018	0.6045	0.99665	SIRA
34040	206.5057	0.799451	0.9839	0.901	0.81696	0.0075	0.0021	0.6674	0.99571	SIRA
34165	206.6506	0.725221	0.9817	0.8658	0.80256	0.0077	0.002	0.6441	0.99574	SIRA
34033	206.7953	0.73419	0.9869	0.933	0.8603	0.0072	0.0024	0.7401	0.99566	SIRA
34047	206.8507	0.766188	0.987	0.8942	0.79848	0.0077	0.0019	0.6376	0.99596	SIRA
34002	206.9399	0.797524	0.9892	0.9401	0.85275	0.0072	0.0024	0.7272	0.9979	SIRA
34019	207.0814	0.806803	0.99	0.907	0.80827	0.0076	0.002	0.6533	0.99669	SIRA
34101	207.2627	0.771353	0.9894	0.8986	0.81024	0.0076	0.002	0.6565	0.99608	SIRA
34281	207.7107	0.811422	0.9884	0.9208	0.84633	0.0072	0.0023	0.7163	0.99703	SIRA
34420	208.1577	0.740738	0.9887	0.8936	0.78381	0.0078	0.0018	0.6144	0.99716	SIRA
34376	208.3655	0.800672	0.9919	0.9541	0.87632	0.007	0.0025	0.7679	0.99657	SIRA
34507	208.4052	0.777747	0.9886	0.8905	0.80733	0.0076	0.002	0.6518	0.99737	SIRA
34931	208.5091	0.762664	0.9775	0.6886	0.84191	0.0073	0.0022	0.7088	0.99664	SIRA
34559	208.6403	0.730066	0.9893	0.9096	0.8377	0.0073	0.0022	0.7017	0.99877	SIRA
34724	208.7898	0.72489	0.986	0.881	0.81613	0.0075	0.002	0.6661	0.99726	SIRA
34685	208.802	0.824711	0.9872	0.9249	0.84324	0.0072	0.0023	0.711	0.99427	SIRA
35078	209.4626	0.752544	0.9824	0.8878	0.82433	0.0074	0.0021	0.6795	0.99773	SIRA
35028	209.8694	0.767369	0.9876	0.8935	0.80803	0.0075	0.002	0.6529	0.99658	SIRA
35144	210.0271	0.772877	0.9858	0.8826	0.81041	0.0075	0.002	0.6568	0.9927	SIRA

35079	210.0817	0.777965	0.9881	0.9109	0.83192	0.0073	0.0022	0.6921	0.99653	SIRA
35416	210.0968	0.747671	0.9789	0.8767	0.78314	0.0077	0.0018	0.6133	0.98583	SIRA
35181	210.2452	0.815527	0.9868	0.8899	0.80088	0.0076	0.0019	0.6414	0.99746	SIRA
35370	210.445	0.769518	0.9834	0.8329	0.83446	0.0073	0.0022	0.6963	0.9984	SIRA
35221	210.572	0.716962	0.9888	0.8807	0.79583	0.0076	0.0019	0.6333	0.99581	SIRA
35381	210.6838	0.732149	0.9853	0.8872	0.79799	0.0076	0.0019	0.6368	0.99636	SIRA
35261	210.7745	0.680753	0.9895	0.869	0.76995	0.0078	0.0017	0.5928	0.99562	SIRA
35522	210.7805	0.715686	0.9823	0.8766	0.79725	0.0076	0.0019	0.6356	0.99458	SIRA
35396	210.9254	0.786504	0.9872	0.8913	0.84062	0.0072	0.0022	0.7066	0.99579	SIRA
35507	211.0703	0.768336	0.9854	0.8954	0.82123	0.0073	0.0021	0.6744	0.99606	SIRA
35566	211.3325	0.785881	0.9863	0.8802	0.80944	0.0074	0.002	0.6552	0.98883	SIRA
35497	211.4891	0.814453	0.9896	0.8926	0.78782	0.0076	0.0018	0.6207	0.99668	SIRA
35530	211.5071	0.77583	0.9889	0.9217	0.83567	0.0072	0.0022	0.6983	0.9991	SIRA
35769	211.5583	0.693415	0.9828	0.8716	0.79775	0.0075	0.0019	0.6364	0.9946	SIRA
35600	211.7478	0.765244	0.9892	0.8746	0.78682	0.0076	0.0018	0.6191	0.99708	SIRA
35703	211.85	0.75161	0.9873	0.8877	0.77698	0.0077	0.0017	0.6037	0.99588	SIRA
35849	211.9762	0.719226	0.9844	0.848	0.76736	0.0078	0.0017	0.5888	0.99694	SIRA
35828	212.2433	0.801468	0.9875	0.9142	0.83044	0.0072	0.0021	0.6896	0.99705	SIRA
35949	212.4352	0.736881	0.986	0.8681	0.79243	0.0076	0.0018	0.6279	0.99126	SIRA
35914	212.5071	0.690361	0.9876	0.8795	0.77801	0.0077	0.0017	0.6053	0.99614	SIRA
36062	212.531	0.775499	0.9838	0.8811	0.79644	0.0075	0.0019	0.6343	0.99612	SIRA
35941	212.6209	0.760919	0.9879	0.8775	0.8112	0.0074	0.002	0.658	0.99556	SIRA
36021	212.7855	0.793648	0.9872	0.8911	0.81914	0.0073	0.002	0.671	0.99708	SIRA
36054	212.8124	0.789287	0.9866	0.8854	0.80837	0.0074	0.0019	0.6535	0.99223	SIRA
36022	213.0008	0.69498	0.9892	0.8816	0.81116	0.0074	0.002	0.658	0.99587	SIRA
36020	213.0217	0.777894	0.9895	0.9461	0.83696	0.0071	0.0022	0.7005	0.99756	SIRA
36235	213.3025	0.718705	0.9862	0.9059	0.83449	0.0072	0.0021	0.6964	0.99493	SIRA
36211	213.4725	0.710929	0.9884	0.8915	0.8133	0.0073	0.002	0.6615	0.9972	SIRA
36226	213.5441	0.726972	0.9887	0.8837	0.79167	0.0075	0.0018	0.6267	0.99497	SIRA
36164	213.5799	0.74035	0.9907	0.909	0.79219	0.0075	0.0018	0.6276	0.99825	SIRA
36262	213.699	0.788476	0.9891	0.8943	0.80972	0.0074	0.002	0.6556	0.99848	SIRA

ConvexArea	EquivDiameter	Extent	Solidity	roundness	Compactness	ShapeFactor1	ShapeFactor2	ShapeFactor3	ShapeFactor4	Class
20684	161.2438	0.790187	0.9872	0.9312	0.87823	0.009	0.0033	0.7713	0.99805	DERMASON
20772	161.4174	0.747407	0.9852	0.921	0.84402	0.0093	0.0029	0.7124	0.99905	DERMASON
20825	161.7483	0.759686	0.9867	0.9378	0.87923	0.009	0.0033	0.7731	0.99679	DERMASON
20988	162.3886	0.793525	0.9868	0.9428	0.87269	0.009	0.0032	0.7616	0.99741	DERMASON
21057	162.6824	0.789412	0.9871	0.9136	0.80966	0.0097	0.0026	0.6555	0.99677	DERMASON
21191	163.2917	0.742361	0.9882	0.9345	0.85414	0.0091	0.003	0.7296	0.9992	DERMASON
21462	163.9104	0.746357	0.9832	0.9309	0.88418	0.0088	0.0033	0.7818	0.99242	DERMASON
21587	164.7356	0.762085	0.9874	0.9281	0.84932	0.0091	0.0029	0.7214	0.9988	DERMASON
21590	164.867	0.725974	0.9888	0.9521	0.85871	0.009	0.003	0.7374	0.99798	DERMASON
21731	165.0561	0.77265	0.9846	0.9379	0.8573	0.009	0.003	0.735	0.99894	DERMASON
21737	165.0869	0.724415	0.9847	0.94	0.86341	0.0089	0.0031	0.7455	0.99662	DERMASON
21762	165.372	0.736692	0.987	0.9123	0.83256	0.0092	0.0027	0.6932	0.99852	DERMASON
21808	165.6759	0.728926	0.9885	0.9309	0.83992	0.0091	0.0028	0.7055	0.99812	DERMASON
21820	165.722	0.81246	0.9885	0.9349	0.84321	0.0091	0.0028	0.711	0.99901	DERMASON
21932	165.8449	0.745282	0.985	0.8708	0.79533	0.0097	0.0024	0.6326	0.99784	DERMASON
21993	165.9753	0.761188	0.9838	0.9133	0.86604	0.0089	0.0031	0.75	0.99856	DERMASON
21877	166.0904	0.810914	0.9904	0.9644	0.88738	0.0086	0.0033	0.7874	0.99834	DERMASON
22006	166.2436	0.791035	0.9864	0.9143	0.83404	0.0092	0.0027	0.6956	0.99846	DERMASON
22078	166.4732	0.735959	0.9859	0.949	0.88119	0.0087	0.0032	0.7765	0.99759	DERMASON
22029	166.7178	0.731029	0.991	0.9294	0.82801	0.0092	0.0027	0.6856	0.99645	DERMASON
22107	166.8972	0.747165	0.9896	0.9352	0.82616	0.0092	0.0027	0.6825	0.99862	DERMASON
22267	167.2173	0.780419	0.9863	0.9067	0.81658	0.0093	0.0026	0.6668	0.99881	DERMASON
22426	167.6279	0.683801	0.9841	0.8795	0.80578	0.0094	0.0025	0.6493	0.99325	DERMASON
22445	167.9125	0.72006	0.9866	0.895	0.84326	0.009	0.0028	0.7111	0.98927	DERMASON
22424	167.9656	0.743657	0.9881	0.9463	0.845	0.009	0.0028	0.714	0.99842	DERMASON
22502	167.9808	0.727601	0.9849	0.863	0.76586	0.0099	0.0021	0.5865	0.99284	DERMASON
22701	168.0868	0.773602	0.9775	0.8746	0.82809	0.0091	0.0027	0.6857	0.99461	DERMASON
22459	168.1209	0.734094	0.9884	0.9399	0.86851	0.0087	0.0031	0.7543	0.99615	DERMASON
22532	168.1436	0.725274	0.9855	0.8758	0.81266	0.0093	0.0025	0.6604	0.99238	DERMASON
22438	168.2269	0.719786	0.9906	0.9424	0.84996	0.0089	0.0029	0.7224	0.99339	DERMASON
22505	168.4954	0.73671	0.9908	0.9639	0.87779	0.0086	0.0032	0.7705	0.99868	DERMASON
22620	168.5369	0.742544	0.9863	0.9037	0.84777	0.0089	0.0028	0.7187	0.99128	DERMASON
22596	168.6276	0.799434	0.9884	0.9439	0.83879	0.009	0.0027	0.7036	0.9958	DERMASON
22648	168.9406	0.716624	0.9898	0.8985	0.79237	0.0095	0.0023	0.6278	0.99948	DERMASON

22696	168.9858	0.81155	0.9882	0.9292	0.86066	0.0088	0.003	0.7407	0.99703	DERMASON
22712	169.0649	0.787961	0.9884	0.9166	0.83606	0.009	0.0027	0.699	0.99661	DERMASON
22837	169.0875	0.758589	0.9833	0.8952	0.80431	0.0094	0.0024	0.6469	0.98694	DERMASON
22699	169.1101	0.774731	0.9895	0.9517	0.87712	0.0086	0.0031	0.7693	0.99858	DERMASON
22989	169.9588	0.721734	0.9869	0.9308	0.83032	0.009	0.0026	0.6894	0.99915	DERMASON
22982	169.9625	0.746463	0.9872	0.903	0.8197	0.0091	0.0025	0.6719	0.99848	DERMASON
23033	170.0262	0.73641	0.9858	0.9345	0.81973	0.0091	0.0025	0.672	0.99655	DERMASON
23016	170.0861	0.776707	0.9872	0.9316	0.8455	0.0089	0.0028	0.7149	0.99831	DERMASON
23071	170.1048	0.790662	0.985	0.9407	0.83429	0.009	0.0027	0.696	0.99667	DERMASON
23132	170.1759	0.740638	0.9833	0.9021	0.8652	0.0086	0.003	0.7486	0.99725	DERMASON
23002	170.1871	0.791427	0.989	0.9289	0.83316	0.009	0.0027	0.6942	0.99761	DERMASON
23071	170.2956	0.772049	0.9873	0.9002	0.8312	0.009	0.0026	0.6909	0.99822	DERMASON
23169	170.5234	0.779587	0.9857	0.9041	0.83383	0.009	0.0027	0.6953	0.99304	DERMASON
23192	170.6391	0.788369	0.9861	0.8982	0.82382	0.0091	0.0026	0.6787	0.9952	DERMASON
23207	170.8703	0.806861	0.9881	0.9204	0.82226	0.0091	0.0026	0.6761	0.99751	DERMASON
23222	170.9932	0.766489	0.9889	0.9014	0.791	0.0094	0.0023	0.6257	0.99786	DERMASON
23288	171.1607	0.73128	0.988	0.943	0.8662	0.0086	0.003	0.7503	0.99871	DERMASON
23306	171.1941	0.733151	0.9876	0.8982	0.81831	0.0091	0.0025	0.6696	0.99932	DERMASON
23465	171.1941	0.781994	0.981	0.8647	0.84017	0.0089	0.0027	0.7059	0.99678	DERMASON