

Multiclass Classification of Dry Beans using Artificial Neural Network

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Abstract: An Artificial Neuron Network (ANN) is a computational model that mimics the way neurons in the human brain work. In agriculture, ANN can be used for various tasks, such as disease and insect detection, crop yield forecasting, soil fertility management, seed categorization, and quality evaluation. Marketing and development of sustainable agricultural systems rely on accurate seed classification. One major goal of this research is to create an ANN model that can reliably classify different types of dried bean seeds based on their shared characteristics. Data from the UC Irvine machine learning repository was used for this study. With the use of principal component analysis (PCA), the most informative characteristics of a dataset are isolated. Using the proposed approach, we intend to categorise seven distinct types of dry bean seeds. The suggested ANN model is then trained using the optimally tuned hyperparameters. The ANN model's effectiveness is measured by its confusion matrix, accuracy, precision, Recall, and F1-Score. After extensive testing, it was determined that the ANN with PCA model had the highest classification accuracy for dried bean seeds (94%) and the highest F1-score (95%).

Keywords: ANN, Precision, Recall, Imbalanced data, Multiclass classification.

1. Introduction

One of the world's most consumed foods, dry beans have been around for at least ten thousand years. These are commercially and nutritionally

significant due to their widespread cultivation. They belong to the Leguminosae family and play a crucial role in the diets of humans. Protein, fiber, antioxidants, and complex carbs can all be abundant in beans. The varied yet necessary nutritional components help make up a balanced diet. They help keep the body running smoothly and help you maintain a healthy lifestyle¹. High-quality seeds are essential for farmers to maximise productivity and manage pests and diseases. Sorting seeds by hand is a laborious procedure. Also, this approach is slow and inefficient when dealing with a lot of stuff. For these reasons, automatic seed grading and categorization systems are essential. Chen *et al.*² investigated five different varieties of maize grain (BAINUO 6, NONGDA 86, NONGDA 108, GAOYOU 115, and NONGDA 4967). Using Mahalanobis distance analysis, they first divided maize grains into three types: white, yellow, and mixed maize. Later, they retrieved 58 different traits from different variations of the same type of maize, of which 17 were responsible for geometry, 13 for shape, and 28 for colour. Using an improved Backpropagation Neural Network (BPNN) technique, the aforementioned maize grains were discovered with classification accuracies of 100 percent, 94 percent, 92 percent, 88 percent, and 100 percent, respectively. Kiratiratanapruk and Sinthupinyo³ suggested a method for classifying more than 10 types of seed defects using colour and texture cues and a support vector machine (SVM) type classifier. Image capture equipment is used to handle massive volumes of seed samples. Color histograms in RGB(RedGreenBlue) and HSV(HueSaturationValue) colour spaces, as well as texture based on Grey level co-occurrence matrix (GLCM) and Local binary pattern (LBP), are used as features in the picture classification section. More than 10,000 sample photos of a normal seed type and 13 defect seed types were used to evaluate the suggested systems. Accuracy is 95.6% for normal seed types and 80.6% for a group of defect seed types. Cakmak and Boyaci⁴ developed a CVS integrated with ANN to assess the quality of chickpeas based on their dimensions, hue, and topographical features. We use a flatbed scanner to capture digital photos of chickpeas. Chickpea properties such as size, colour, and morphology are also extracted for analytic image processing. The findings of the experiments demonstrate that the success rates for evaluating colour, surface morphology, and form are 95.4%, 87.6%, and 96.0%, correspondingly. Experiments showed that the results of ANN-integrated CVS were highly correlated with those obtained by calipers or qualified inspectors. Haider *et al.*⁵ used seven different date fruit types to test the k-nearest neighbor (cityblock), k-nearest neighbour (Euclidean), discriminant analysis, and neural networks classification methods by appropriately generating 15 different visual features

on the image data. As a result, the maximum accuracy rates achieved vary between 89% and 99%. Alrajeh and Alzohairy⁶ offer a new ANN-based date fruit sorting system. The goals of this study are to establish a set of external quality criteria based on form and colour for various types of date fruit photographs and to assess the efficiency of the features. For image classification, two alternative neural network models were used as classifiers: multi-layer perceptron (MLP) with backpropagation and radial basis function RBF networks. In the performance evaluation studies, the neural networks acquired a recognition rate of 87.5% and 91.1% for MLP with backpropagation and RBF, respectively, which is consistent with the best findings reported in the literature for the identical data set and testing paradigms. This article by Vibhute and Bodhe⁷ provides a comprehensive overview of the many image processing techniques and CVS that have been used to categorise diverse seed kinds during the past decade. This way, different seed types can be sorted according to their quality, colour, and size. These analyses usually make use of visual cues such as seed colour, shape, and morphology. N Pandey *et al.*⁸ suggested a method that employs content-based image retrieval (CBIR) to identify wheat and gram based on their attributes. From 200 wheat and gramme photos, another 25 shape, colour, and statistical attributes are extracted. Of the 200 photos, 150 are used for training and 50 are used for testing. According to the suggested system. Image recognition employs both the Euclidean distance and artificial neural network techniques. The system is 95% accurate when using ANN and 84.4 percent accurate when utilising the Euclidean distance approach. Using Backpropagation ANN, Chaugule and Mali⁹ analysed texture and shape features for categorising paddy varieties. This study employs the paddy varieties Karjat-6(K6), Ratnagiri-2(R2), Ratnagiri-4(R4), and Ratnagiri-24(R24). Texture, shape, and texture and shape features were retrieved from photographs of individual grains and evaluated for grain categorization. The accuracy of texture, shape and texture-n-shape features is 82.61%, 88.00%, and 87.27%, respectively. The shape feature set outperformed the texture feature set. Kurtulmus *et al.*¹⁰ proposed a neural network and computer vision-based classification scheme to distinguish between eight pepper seed varieties. Image of pepper seeds was used to extract colour, shape, and texture properties used to build the feature database. We chose more attractive features using sequential feature selection with alternate criterion functions. We used cross-validation guidelines to avoid overfitting and produce a trustworthy classification model. Using sequential feature selection and the MLP with resilient backpropagation, we could classify eight different types of pepper seeds with an accuracy of 84.94%. Sabanci *et al.*¹¹ employed an

ANN-based CVS to categorise bread and durum wheat grains. The researchers collected 21 attributes from each of 100 bread samples and 100 durum wheat grains. They utilized the Holdout approach to differentiate the two wheat varieties, which split their data into 90 percent training and 10 percent testing. Using the developed ANN model, we could achieve a 99.92% success rate in our categorization efforts.

A quality and purity monitoring expert system for grapes was created by Karimi *et al.*¹² by using the GLCM, GLRM (matrix of grey levels), and LBP. From a dataset of 1400 images of raisins, 146 surface characteristics were extracted. They used principal component analysis (PCA) to determine the most valuable aspects of these elements. Using the top 50 features, they found that the SVM method yielded more effective and precise classification findings than the ANN method. Li *et al.*¹³ present a method for accurately classifying peanuts. Peanuts are divided into three categories: one, two, and three. Three distinct methods were used to extract the features of peanut images, including the convolution neural network of aspect ratio, HOG, and Hu invariant moment. Then peanut images were classified using the SVM (support vector machine). The accuracy rates of the aspect ratio + SVM algorithm, HOG+SVM algorithm, and Hu invariant moment +SVM algorithm are 96.72%, 81.97%, and 81.97%, respectively. Cinar and Koklu¹⁴ provided an artificial intelligence-based approach for classifying two rice varieties, Osmancik and Cammeo. The CVS technology was used to capture photos of 3810 rice grains from the two species. In addition, 7 morphological characteristics were acquired for each grain of rice. Models were built with these characteristics using LR, MLP, SVM, DT, RF, NB, and k-NN machine learning approaches, and performance measurement values were acquired. The classification success rates were 93.02% (LR), 92.86% (MLP), 92.83% (SVM), 92.49% (DT), 92.39% (RF), 91.71% (NB), and 88.58% (k-NN). In the recent literature, many authors¹⁵⁻¹⁸ have focused on different seed classification using machine learning algorithms and ANN.

When it comes to the family (Fabaceae- Leguminosae), the dry bean (*Phaseolus vulgaris* L) is by far the most commercially important and widely cultivated species. Classification of dried bean seeds is a topic that numerous authors have explored. Kilic *et al.*¹⁹ established a CVS for bean quality control that accounts for the size and amount of colour variation present in sample data. To determine the hue of beans, they turned to artificial neural networks. The acquired samples were divided into five groups based on their classification by the algorithm and the experts. The ANN was put to the test with data from 371. The overall accuracy of the system's classification is 90.6%. Using digital photographs of 12 different bean kinds, Kara *et al.*²⁰

estimated bean size and shape using an image processing approach. These properties are used to divide beans into several categories. This research shows that bean types vary in terms of size, shape, and physical traits. Using a combination of supervised and unsupervised machine learning techniques, Koklu and Ozkan²¹ created a model for categorising seven different types of a dried bean seed. Using seven different types of dried beans, they collected 13611 individual images to use as a dataset. In addition, 16 geometrical features are extracted during the preprocessing phase of the process and then used for classification via Multilayer perceptron (MLP), Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Decision Tree (D.T.), with respective accuracy rates of 91.73%, 93.13%, 87.92%, and 92.52%. SVM performed best for categorising the dry-been types among the aforementioned models.

Dry bean classification using principal component analysis and artificial neural networks is presented here. The following session will go through general performance measures for binary and multiclass classifications. Section 3 describes the data pretreatment and analysis. Section 4 outlines the construction and training of the proposed ANN model for recognising and categorising dry beans. Section 5 covers the ANN model's outputs. The final section,6, wraps up the whole work.

2. Evaluation criteria

Evaluating the results of a machine learning model is crucial to its success. Performance metrics and evaluation metrics are different ways of measuring the quality and efficacy of a model. Measuring how well a model fits the data is possible with the help of these performance indicators. When data needs to be sorted into groups, we have a classification problem. The model is trained on the provided dataset and then used for the task of categorising additional data or groups. The quality of a model can be judged by the proportion of its predictions that turn out to be accurate. On the other hand, this data just proves that the categorisation is right. In most cases, the classification accuracy alone is insufficient to establish whether a model is adequate because there is no information regarding the number of misclassified instances. A classifier's estimation results can be explained with the help of the confusion matrix.

When describing the effectiveness of a classification model on a given set of test data, a confusion matrix is a common manner of presentation. True positives, true negatives, false positives, and false negatives are the four facets that make up this metric. The confusion matrix for binary classification may be found in Table III and is comprised of the four parameters listed below²².

True Positives (tp): The number of positive instances that are correctly classified.

True negatives (tn): The number of negative instances that are correctly classified.

False positives (fp): The number of negative instances that are misclassified.

False negatives (fn): The number of positive instances that are misclassified.

To evaluate and scale the model, the success criteria such as Accuracy, Precision, Recall and F1-Score are calculated for binary-class data sets, using Table III. The calculation formula and explanation for these metrics are given below.

Accuracy: The accuracy metric measures the ratio of correctly predicted samples over the total number of samples evaluated.

$$(2.1) \quad \text{Accuracy} = \frac{tp+tn}{tp+fp+tn+fn}$$

Precision(p): The ratio of correctly predicted positive samples to estimated total positive samples. This is also called a Positive Predictive Value.

$$(2.2) \quad p = \frac{tp}{tp+fp}$$

Recall (r): It is used to measure the fraction of positive samples that are correctly classified.

$$(2.3) \quad r = \frac{tp}{tp+fn}$$

F1-Score (F.M.): The harmonic mean of precision and Recall. Therefore, it takes into account both false positives and false negatives. Especially in cases of irregular class distribution, looking at the F1-score may be more beneficial than looking at the accuracy.

$$(2.4) \quad FM = \frac{2*p*r}{p+r}$$

Table IV shows the confusion matrix and its representation for multiple classes (see Hossin and Sulaiman²²). The calculation formula and explanation for these metrics are given below.

Averaged Accuracy: It is used to calculate the mean success of classes.

$$(2.5) \quad \text{Averaged accuracy} = \frac{\sum_{i=1}^l \frac{tp_i+tn_i}{tp_i+fp_i+tn_i+fn_i}}{l}$$

Averaged precision (pM) : It is used to calculate the mean of the precision per class.

$$(2.6) \quad pM = \frac{\sum_{i=1}^l \frac{tp_i}{tp_i+fp_i}}{l}$$

Averaged Recall (rM): It is used to calculate the mean of the Recall per class.

$$(2.7) \quad rM = \frac{\sum_{i=1}^l \frac{tp_i}{tp_i + tn_i}}{l}$$

F1-Score (Averaged F-Measure): It is used to calculate the mean of the F1-Score per class.

$$(2.8) \quad FM = \frac{2 * pM * rM}{pM + rM}$$

3. Data Analysis and Preprocessing

3.1. Data Analysis

This study analysed the form, shape, type, and structure of seven dried bean varieties: Seker, Barbunya, Bombay, Cali, Dermosan, Horoz, and Sira. Dry beans have these essential traits: Cali seeds are kidney-shaped, dense, and white. Long, tubular, white Horoz species are medium-sized. Dermason kinds are larger, flatter, white, and round. Seker seeds are huge white spheres. Bombay seeds are huge, white, oval, and swollen. Barbunya seeds are big, oval to circular, and brown with red bands or variegated, speckled designs. Sira seeds are tiny, white, flat, and have one flat and one round end. An in-built computer vision device took 236 dried bean images. Preprocessing and segmentation yielded 13611 dry bean images. A numerical list of dry bean datasets was created. There are 13611 samples from the dry bean dataset that are being considered. The bean species is labelled, and a sample is comprised of 16 geometric shapes. Participating species include the Barbunya, Bombay, Cali, Dermason, Horoz, Seker, and Sira. There are a total of 16 geometric properties, including the standard 12 dimensions (area, perimeter, major axis length, minor axis length, aspect ratio, eccentricity, convex area, Equiv diameter, extent, solidity, roundness, and compactness) and four additional dimensions (shape factors 1,2,3 and 4). (For details see Koklu and Ozkan¹²¹).

The bean's colour cannot be determined from the geometric data. Figure 1 illustrates how unbalanced the data set is. For example, the "Dermason" bean is over-sampled, whereas the "Bombay" bean is under-sampled. A look at Table I reveals that all but one of the features store numbers (int and float types), while the lone "object" type feature represents different varieties of dry beans. There are no blanks in this data collection.

3.2. Data Preprocessing

The information must be processed further before a synthetic neural network can use it. In the initial data preparation stage, the dataset is separated into features and associated labels. In order to codify the "one-hot" designation,

the bean species were assigned numbers from 0 to 6, and these numbers were then assigned to the beans. Chollet²³ provides a thorough explanation of why "one-hot" encoding is used. Scaling, or normalisation of the training data, is the other process. Each feature's data is normalised so that it is centered at zero (by subtracting the mean and dividing by the standard deviation). Some studies have found that implementing standards might reduce training time and lead to better results.

4. Model development

A categorization model plays a crucial part in automated decision-making systems. The model is helpful for sorting features into their proper categories. In the scientific literature, many different categorization algorithms are utilised. They may produce inconsistent outcomes depending on the data set being analysed. As a result, it is crucial to pick the best classifier based on the information gathered. For the purpose of classifying dry beans based on their attributes, a Feedforward ANN model is constructed in this research.

4.1 ANN without PCA

Neurons are stacked on several levels to create the ANN's structure. These non-linearly functioning neurons are linked together through synaptic weights. During training, these weights are adjusted so that the output of the ANN is as close as possible to the desired classification of the dry beans into seven classes based on their geometrical properties. Figure 2 depicts the study's ANN architecture, and Table IV summarises the network's parameters. The ANN model has a single input layer, three hidden layers, and an output layer.

The dataset is partitioned into a training set (80% of the data) and a test group (20% of the data). The training set is used to optimise the ANN model's weights, while the test set is used to evaluate the model's accuracy on unknown data.

Initially, the input layer receiving the input feature x_i passes the information to a hidden layer with some randomly initialized weights w_i . In the hidden layer, all the inputs are multiplied with their assigned weight values w_i and added with a bias value b to produce the net input represented by z as in equation (4.1).

$$(4.1) \quad Z = \sum_{i=1}^n x_i w_i + b$$

The net input z is passed through an activation function g to produce the hidden layer output $y = g(z)$ and is represented as in equation (4.2).

$$(4.2) \quad y = g(z) = g(\sum_{i=1}^n x_i w_i + b)$$

Activation functions in input and hidden layers employ the Rectified Linear Unit (ReLU), which is represented as below

$$(4.3) \quad y = g(z) = \max(0, z)$$

During the training process overfitting can be mitigated in neural networks with the help of the dropout, as reported by Srivastava *et al.*²⁴ Overfitting is especially troublesome for ANNs. If your model does exceptionally well at making predictions on the training data but fares poorly on the test data, this is the situation. Dropout is a regularisation technique that can be used to fix this problem. Dropout refers to the elimination of neurons in a neural network (both from the input and hidden layers). This scheme makes use of two dropout levels, each with a probability of $p = 0.1$.

The training of neural networks can be made faster and more stable by adding more levels to the network, as in the "batch normalisation" method. The result of each layer is fed into a standardizer and a normalizer in preparation for the next layer. Batch normalisation is described in detail in Bjorck²⁵.

After passing the input through all the hidden layers, the final output layer is used to provide the seven different kinds of bean neurons (one each) make up the output layer. The activation function for the final layer is softmax, which is defined as in equation (4.4).

$$(4.4) \quad S(y)_i = \frac{\exp(y_i)}{\sum_{j=1}^n \exp(y_j)}$$

Where y is the input vector to a softmax function S , y_i values are the elements of the input vector, $\exp(y_i)$ is the standard exponential function is applied to each element of the input vector, n is the number of classes, $\sum_{j=1}^n \exp(y_j)$ is a normalization term, which ensures that all the output values of the function will sum to 1 and each be in the range (0, 1), thus constituting a valid probability distribution.

After training, the Error value EV using cross entropy is computed for each output to its actual output as shown below,

$$(4.5) \quad EV = -\sum_{i=0}^n t_i \log(p_i)$$

where t_i is the truth label (Actual values) and $\log(p_i)$ is the softmax probability for the i^{th} class (Predicted values).

To get the best performance of the model, the training process requires backpropagation to minimize the error by updating weights and biases using the Adam optimizer. The optimised weights and biases are obtained and updated to the classification network as a result of this optimizer.

4.2.ANN with PCA

Principal Component Analysis (PCA) is a statistical method for reducing the dimension of a dataset by identifying and emphasising its most essential characteristics. The features are chosen according to the amount of variation they introduce into the final product. The first principal component is the factor that creates the most dispersion. The second highest-variance contributing factor is the second principal component, and so on. It's worth noting that P.C.s have no inherent relationship with one another.

The feature set's train and test datasets are subjected to principal component analysis. Figure 3 demonstrates that when the number of components is reduced to 10, 99% of the original variation remains. So, we train and test the same ANN model as before with only 10 input features. The number of trainable parameters has been cut down as well.

5. Results and Discussions

Confusion matrices are a convenient method of visualising results and contrasting observed and predicted values. Figure 4 shows the confusion matrix for the proposed ANN model using principal component analysis. Most conversions went wrong between Dermason and Sira (34 + 49). Bombay, on the other hand, was placed in the correct category, which is to be expected. Bombay beans are much more widespread than other varieties very quickly. Table V displays the model's generated classification performance measures, including accuracy, precision, Recall, and F1-score. Significantly, the F1-Score value is high in the classification model because it measures the classifier's performance. It is also clear that the accuracy is proportional to the number of correctly identified positives, which is determined by the Precision value in the positive direction. Table V demonstrates that a complete classification of the Bombay variety is possible with a high degree of certainty. The Sira variety ranks last in the accuracy of classification. In addition, the confusion matrix shows that the Dermason and Sira variants do poorly in terms of discrimination. A comparison of the proposed model's accuracy and loss on the training and test datasets is depicted in Figure 3. The accuracy and loss figures for the training sets are comparable to those for the test sets. A look at Table VI reveals that the ANN model using PCA achieves superior results, with an average accuracy of 94% and an F1-Score of 95%.

To categorise dry beans, the authors²¹ created the Multilayer Perceptron (MLP), Support Vector Machine (SVM), k-Nearest Neighbor (KNN), and Decision Tree (D.T), which achieved an accuracy of 91.73%, 93.13%, 87.92% and 92.52%. In comparison, the proposed ANN model performs better with fewer features.

6. Conclusion

The consistency and quality of seeds depend on their classification, which is why it's crucial to identify the many types of dry bean seeds available. This research demonstrates that the F1-Score and model accuracy are highly correlated. The data appear to have a regular distribution. Success rates for classifying dry beans using the model are quite high across the board. Since the Sira bean variety is not easily distinguished from the Dermason bean variety, it is clear that the Sira variety has the worst sorting performance. With fewer trainable parameters and fewer input features, the PCA-augmented ANN model achieves a higher F1-score (average F1-score) and accuracy (average accuracy) (95%). Additional information, like texture and statistics, can be added to current shape and size features to enhance classification in the future.

Table I: Attributes of the Dry bean dataset and their type

#	Column	Non-Null Count	Dtype
0	Area	13611 non-null	int64
1	Perimeter	13611 non-null	float64
2	MajorAxisLength	13611 non-null	float64
3	MinorAxisLength	13611 non-null	float64
4	AspectRatio	13611 non-null	float64
5	Eccentricity	13611 non-null	float64
6	ConvexArea	13611 non-null	float64
7	EquivDiameter	13611 non-null	float64
8	Extent	13611 non-null	float64
9	Solidity	13611 non-null	float64
10	roundness	13611 non-null	float64
11	Compactness	13611 non-null	float64
12	ShapeFactor1	13611 non-null	float64
13	ShapeFactor2	13611 non-null	float64
14	ShapeFactor3	13611 non-null	float64
15	ShapeFactor4	13611 non-null	float64
16	Class	13611 non-null	object

Table II: Confusion Matrix representation for binary classes

		Predicted	
		Positive	Negative
Actual	Positive	True Positive(tp)	False Negative (fn)
	Negative	False Positive(fp)	True Negative (tn)

Table III: Confusion Matrix representation for multiple classes

		Predicted			
			C2	...	Cn
Actual	C1	T1	F12	...	F1n
	C2	F21	T2	...	F2n
	...	...	...	...	...
	Cn	Fn1	Fn2	...	Tn

Table IV: MLP Parameters

Parameter Name	Parameter
Hidden Layer number	3
Batch Normalization Layer number	3
Dropout Layer number	2
Hidden Layer Activation function	Relu
Output Layer Activation function	Softmax
Learning Rate	0.001
Maximum Number of Epochs to Train	500
Optimizer	Adam

Table V:Classification report showing values for different performance metrics for ANN with PCA.

	Precision	Recall	F1-score	Support
Barbunya	95	93	94	268
Bombay	1.00	1.00	1.00	110
Cali	0.97	0.95	0.96	336
Dermason	0.91	0.95	0.93	702
Haroz	0.97	0.96	0.97	406
Seker	0.96	0.97	0.97	406
Sira	0.89	0.86	0.87	516
Accuracy			0.94	2723
Macro Average	0.95	0.94	0.95	2723
Weighted Average	0.94	0.94	0.94	2723

Table VI: Comparison between 2 ANN Models

Model	Accuracy	F1-Score
ANN without PCA	93	94
ANN with PCA	94	95

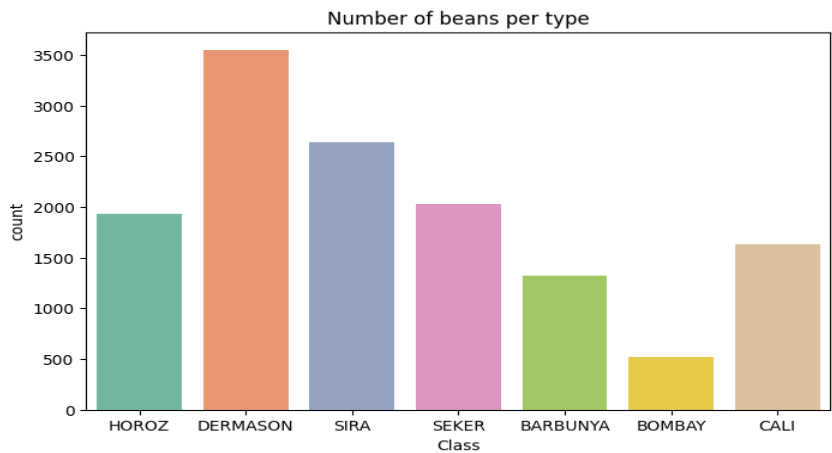


Figure 1: Distribution of different types of beans in the dry bean dataset

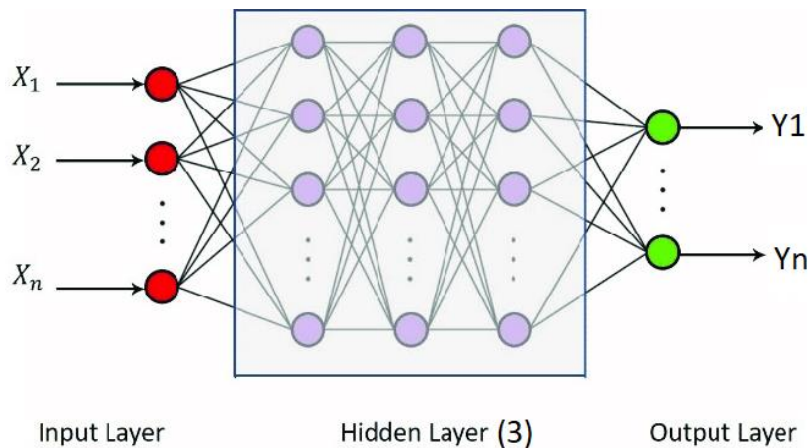


Figure 2: ANN architecture used in this study

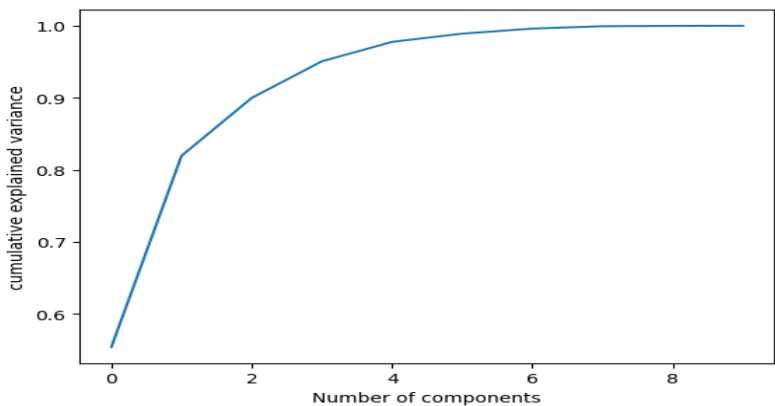


Figure 3:PCA components and their cumulative explained variance.

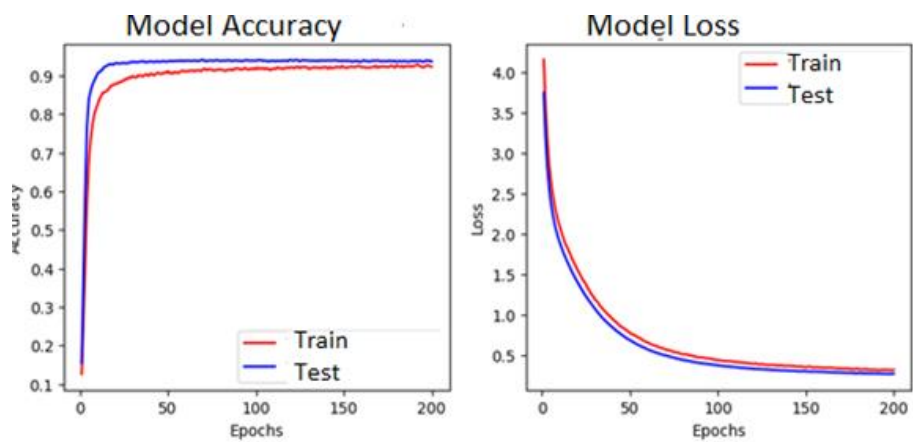


Figure 4: Train vs test accuracy(left) and Loss (right) for ANN with PCA

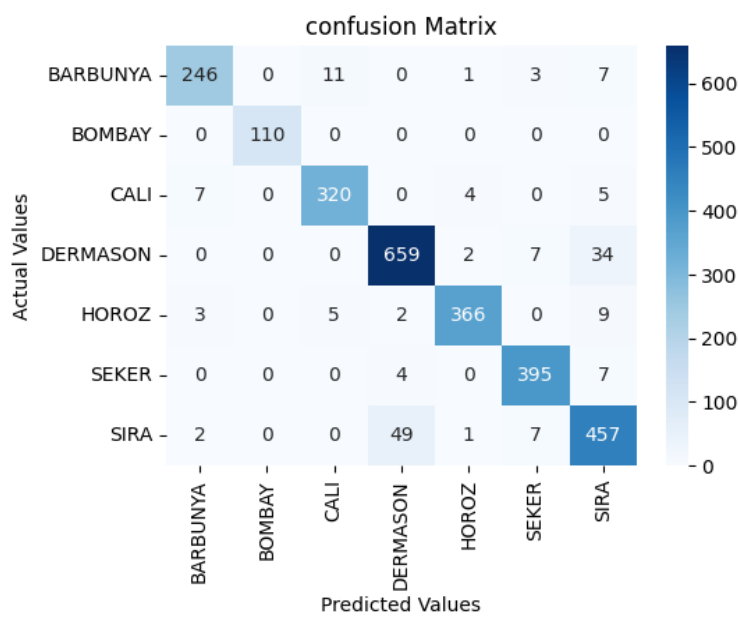


Figure 5: Confusion matrix for the test set of ANN with PCA.

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